

Documentation of the DIGRAPH3 software collection



A. Tutorials of the DIGRAPH3 Resources

HTML Version

The tutorials in this document describe the practical usage of our *Digraph3* Python3 software resources in the field of *Algorithmic Decision Theory* and more specifically in **outranking** based *Multiple Criteria Decision Aid* (MCDA). They mainly illustrate practical tools for a Master Course at the University of Luxembourg. The document contains first a set of tutorials introducing the main objects available in the Digraph3 collection of Python3 modules, like **bipolar-valued digraphs**, **outranking digraphs**, and **multicriteria performance tableaux**. The second and methodological set of tutorials is decision problem oriented and shows how to edit multicriteria performance tableaux, how to compute the potential **winner(s)** of an election, how to build a **best choice recommendation**, and how to **rate** or **linearly rank** with multiple incommensurable performance criteria. We finally discuss the **fair intergroup** and **intragroup pairing** problems. A third part presents three **evaluation** and **decision case studies**. A fourth and fifth part present tools for working with big performance tableaux and digraphs. The last part is devoted to **undirected graphs** with a tutorial on how to compute **non isomorphic maximal independent sets** (kernels) in the n-cycle graph. Special tutorials are finally introducing **perfect** graphs, like *split*, *interval* and *permutation* graphs.

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1 Working with digraphs and outranking digraphs

This first part of the tutorials introduces the Digraph3 software collection of Python programming resources.

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1.1 Working with the *Digraph3* software resources

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Purpose

The basic idea of the *Digraph3* Python resources is to make easy python interactive sessions or write short Python3 scripts for computing all kind of results from a bipolar-valued digraph or graph. These include such features as best-choice recommendations, linear rankings, performance ratings, fair pairings, etc. Most of the available computing resources are meant to illustrate a Master Course on *Algorithmic Decision Theory* given at the University of Luxembourg in the context of its *Master in Information and Computer Science* (MICS).

The Python development of these computing resources offers the advantage of an easy to write and maintain OOP source code as expected from a performing scripting language without loosing on efficiency in execution times compared to compiled languages such as C++ or Java.

Downloading of the *Digraph3* resources

Using the *Digraph3* modules is easy. You only need to have installed on your system the [Python](https://www.python.org/doc/) (<https://www.python.org/doc/>) programming language of version 3.+ (readily available under Linux and Mac OS).

Several download options (easiest under Linux or Mac OS-X) are given.

1. (*Recommended*) With a browser access, download and extract the latest distribution zip archive from

<https://github.com/rbisdorff/Digraph3> or, from

<https://sourceforge.net/projects/digraph3>

2. By using a git client either, cloning from github

```
...$ git clone https://github.com/rbisdorff/Digraph3
```

3. Or, from sourceforge.net

```
...$ git clone https://git.code.sf.net/p/digraph3/code Digraph3
```

Starting a Python3 terminal session

You may start an interactive Python3 terminal session in the *Digraph3* directory.

```
1 $HOME/.../Digraph3$ python3
2 Python 3.12.3 (main, Aug 14 2025, 17:47:21) [GCC 13.3.0] on linux
```

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```
3 Type "help", "copyright", "credits" or "license" for more information.  
4 >>>
```

For exploring the classes and methods provided by the *Digraph3* modules (see the [Reference manual](#)) enter the *Python3* commands following the session prompts marked with `>>>` or `... .`. The lines without the prompt are console output from the *Python3* interpreter.

Listing 1.1: Generating a random digraph instance

```
1 >>> from randomDigraphs import RandomDigraph  
2 >>> dg = RandomDigraph(order=5,arcProbability=0.5,seed=101)  
3 >>> dg  
4 *----- Digraph instance description -----*  
5 Instance class : RandomDigraph  
6 Instance name : randomDigraph  
7 Digraph Order : 5  
8 Digraph Size : 12  
9 Valuation domain : [-1.00; 1.00]  
10 Determinateness : 100.000  
11 Attributes : ['actions', 'valuationdomain', 'relation',  
12 'order', 'name', 'gamma', 'notGamma',  
13 'seed', 'arcProbability', ]
```

In Listing 1.1 we import, for instance, from the `randomDigraphs` module the `RandomDigraph` class in order to generate a random *digraph* object `dg` of order 5 - number of nodes called (decision) *actions* - and arc probability of 50%. We may directly inspect the content of python object `dg` (Line 3).

Note

For convenience of redoing the computations, all python code-blocks show in the upper right corner a specific **copy button** which allows to both copy *only* code lines, i.e. lines starting with '`>>>`' or '`... .`', and stripping the console prompts. The copied code lines may hence be right away *pasted* into a Python console session. As of Python 3.13.+ it is necessary to switch in the python terminal console with the F3 function key into a console "*paste mode*" which allows pasting blocks of code. Press F3 key again to return to the regular prompt (see Python 3.13.+ Interactive Mode documentation).

Digraph object structure

All *Digraph* objects contain at least the following attributes (see Listing 1.1 Lines 11-12):

0. A **name** attribute, holding usually the actual name of the stored instance that was used to create the instance;

1. A ordered dictionary of digraph nodes called **actions** (decision alternatives) with at least a ‘name’ attribute;
2. An **order** attribute containing the number of graph nodes (length of the actions dictionary) automatically added by the object constructor;
3. A logical characteristic **valuationdomain** dictionary with three decimal entries: the minimum (-1.0, means certainly false), the median (0.0, means missing information) and the maximum characteristic value (+1.0, means certainly true);
4. A double dictionary called **relation** and indexed by an oriented pair of actions (nodes) and carrying a decimal characteristic value in the range of the previous valuation domain;
5. Its associated **gamma** attribute, a dictionary containing the direct successors, respectively predecessors of each action, automatically added by the object constructor;
6. Its associated **notGamma** attribute, a dictionary containing the actions that are not direct successors respectively predecessors of each action, automatically added by the object constructor.

Permanent storage

The `save()` method stores the digraph object `dg` in a file named ‘tutorialDigraph.py’,

```
>>> dg.save('tutorialDigraph')
---- Saving digraph in file: <tutorialDigraph.py> ----
```

with the following content

```

1 from decimal import Decimal
2 from collections import OrderedDict
3 actions = OrderedDict([
4     ('a1', {'shortName': 'a1', 'name': 'random decision action'}),
5     ('a2', {'shortName': 'a2', 'name': 'random decision action'}),
6     ('a3', {'shortName': 'a3', 'name': 'random decision action'}),
7     ('a4', {'shortName': 'a4', 'name': 'random decision action'}),
8     ('a5', {'shortName': 'a5', 'name': 'random decision action'}),
9 ])
10 valuationdomain = {'min': Decimal('-1.0'),
11                     'med': Decimal('0.0'),
12                     'max': Decimal('1.0'),
13                     'hasIntegerValuation': True, # repr. format
14                     }
15 relation = {
16     'a1': {'a1':Decimal('-1.0'), 'a2':Decimal('-1.0'),
17             'a3':Decimal('1.0'), 'a4':Decimal('-1.0'),
18             'a5':Decimal('-1.0'),},
19     'a2': {'a1':Decimal('1.0'), 'a2':Decimal('-1.0'),
20             'a3':Decimal('-1.0'), 'a4':Decimal('1.0'),}
```

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```
21     'a5': Decimal('1.0'),},
22     'a3': {'a1':Decimal('1.0'), 'a2':Decimal('-1.0'),
23             'a3':Decimal('-1.0'), 'a4':Decimal('1.0'),
24             'a5':Decimal('-1.0'),},
25     'a4': {'a1':Decimal('1.0'), 'a2':Decimal('1.0'),
26             'a3':Decimal('1.0'), 'a4':Decimal('-1.0'),
27             'a5':Decimal('-1.0'),},
28     'a5': {'a1':Decimal('1.0'), 'a2':Decimal('1.0'),
29             'a3':Decimal('1.0'), 'a4':Decimal('-1.0'),
30             'a5':Decimal('-1.0'),},
31 }
```

Inspecting a *Digraph* object

We may reload (see Listing 1.2) the previously saved digraph object from the file named ‘tutorialDigraph.py’ with the `Digraph` class constructor and different `show` methods (see Listing 1.2 below) reveal us that `dg` is a *crisp, irreflexive* and *connected* digraph of *order* five.

Listing 1.2: Random crisp digraph example

```
1 >>> from digraphs import Digraph
2 >>> dg = Digraph('tutorialDigraph')
3 >>> dg.showShort()
4 *----- show short -----*
5 Digraph          : tutorialDigraph
6 Actions          : OrderedDict([
7     ('a1', {'shortName': 'a1', 'name': 'random decision action'}),
8     ('a2', {'shortName': 'a2', 'name': 'random decision action'}),
9     ('a3', {'shortName': 'a3', 'name': 'random decision action'}),
10    ('a4', {'shortName': 'a4', 'name': 'random decision action'}),
11    ('a5', {'shortName': 'a5', 'name': 'random decision action'})
12 ])
13 Valuation domain : {
14     'min': Decimal('-1.0'),
15     'max': Decimal('1.0'),
16     'med': Decimal('0.0'), 'hasIntegerValuation': True
17 }
18 >>> dg.showRelationTable()
19 * ----- Relation Table -----
20   S | 'a1'  'a2'  'a3'  'a4'  'a5'
21   ---|-----
22   'a1' | -1    -1    1    -1    -1
23   'a2' |  1    -1    -1    1    1
24   'a3' |  1    -1    -1    1    -1
25   'a4' |  1     1    1    -1    -1
```

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```

26   'a5' | 1 1 1 -1 -1
27 Valuation domain: [-1;+1]
28 >>> dg.showComponents()
29 *--- Connected Components ---*
30 1: ['a1', 'a2', 'a3', 'a4', 'a5']
31 >>> dg.showNeighborhoods()
32 Neighborhoods:
33   Gamma :
34 'a1': in => {'a2', 'a4', 'a3', 'a5'}, out => {'a3'}
35 'a2': in => {'a5', 'a4'}, out => {'a1', 'a4', 'a5'}
36 'a3': in => {'a1', 'a4', 'a5'}, out => {'a1', 'a4'}
37 'a4': in => {'a2', 'a3'}, out => {'a1', 'a3', 'a2'}
38 'a5': in => {'a2'}, out => {'a1', 'a3', 'a2'}
39   Not Gamma :
40 'a1': in => set(), out => {'a2', 'a4', 'a5'}
41 'a2': in => {'a1', 'a3'}, out => {'a3'}
42 'a3': in => {'a2'}, out => {'a2', 'a5'}
43 'a4': in => {'a1', 'a5'}, out => {'a5'}
44 'a5': in => {'a1', 'a4', 'a3'}, out => {'a4'}

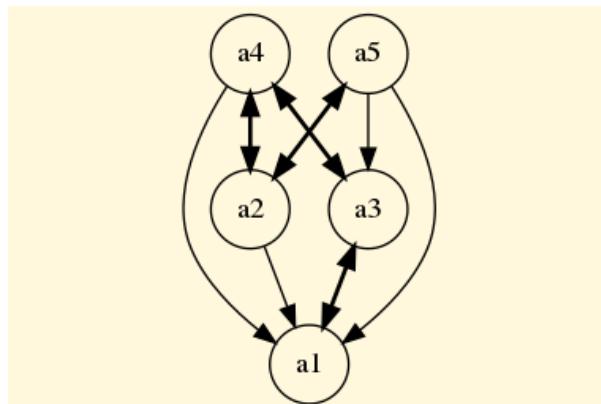
```

The `exportGraphViz()` method generates in the current working directory a ‘tutorialDigraph.dot’ file and a ‘tutorialdigraph.png’ picture of the tutorial digraph `dg` (see Fig. 1.1), if the `graphviz` (<https://graphviz.org/>) tools are installed on your system¹.

```

1 >>> dg.exportGraphViz('tutorialDigraph')
2 *---- exporting a dot file do GraphViz tools -----
3 Exporting to tutorialDigraph.dot
4 dot -Grankdir=BT -Tpng tutorialDigraph.dot -o tutorialDigraph.png

```



Rubis Python Server (graphviz), R. Bisдорff, 2008

Fig. 1.1: The tutorial crisp digraph

¹ The `exportGraphViz` method is depending on drawing tools from `graphviz` (<https://graphviz.org/>). On Linux Ubuntu or Debian you may try ‘sudo apt-get install graphviz’ to install them. There are ready `dmg` installers for Mac OSX.

Further methods are provided for inspecting this Digraph object `dg` , like the following `showStatistics()` method.

Listing 1.3: Inspecting a Digraph object

```

1  >>> dg.showStatistics()
2  *----- general statistics -----*
3  for digraph : <tutorialDigraph.py>
4  order : 5 nodes
5  size : 12 arcs
6  # indeterminate : 0 arcs
7  determinateness (%) : 100.0
8  arc density : 0.60
9  double arc density : 0.40
10 single arc density : 0.40
11 absence density : 0.20
12 strict single arc density: 0.40
13 strict absence density : 0.20
14 # components : 1
15 # strong components : 1
16 transitivity degree (%) : 60.0
17 : [0, 1, 2, 3, 4, 5]
18 outdegrees distribution : [0, 1, 1, 3, 0, 0]
19 indegrees distribution : [0, 1, 2, 1, 1, 0]
20 mean outdegree : 2.40
21 mean indegree : 2.40
22 : [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10]
23 symmetric degrees dist. : [0, 0, 0, 0, 1, 4, 0, 0, 0, 0, 0]
24 mean symmetric degree : 4.80
25 outdegrees concentration index : 0.1667
26 indegrees concentration index : 0.2333
27 symdegrees concentration index : 0.0333
28 : [0, 1, 2, 3, 4, 'inf']
29 neighbourhood depths distribution: [0, 1, 4, 0, 0, 0]
30 mean neighbourhood depth : 1.80
31 digraph diameter : 2
32 agglomeration distribution :
33 a1 : 58.33
34 a2 : 33.33
35 a3 : 33.33
36 a4 : 50.00
37 a5 : 50.00
38 agglomeration coefficient : 45.00

```

These `show` methods usually rely upon corresponding `compute` methods, like the `computeSize()`, the `computeDeterminateness()` or the `computeTransitivityDegree()` method (see Listing 1.3 Line 5,7,16).

```

1 >>> dg.computeSize()
2 12
3 >>> dg.computeDeterminateness(InPercents=True)
4 Decimal('100.00')
5 >>> dg.computeTransitivityDegree(InPercents=True)
6 Decimal('60.00')

```

Mind that *show* methods output their results in the Python console. We provide also some *showHTML* methods which output their results in a system browser's window.

```
>>> dg.showHTMLRelationMap(relationName='r(x,y)',rankingRule=None)
```

Relation Map

Ranking rule: Alphabetic

r(x,y)	a1	a2	a3	a4	a5
a1	-	-	+	-	-
a2	+	-	-	+	+
a3	+	-	-	+	-
a4	+	+	+	-	-
a5	+	+	+	-	-

Semantics	
+	certainly valid
*	valid
/	indeterminate
-	invalid
-	certainly invalid

Fig. 1.2: Browsing the relation map of the tutorial digraph

In Fig. 1.2 we find confirmed again that our random digraph instance *dg*, is indeed a crisp, i.e. 100% determined digraph instance.

Special *Digraph* instances

Some constructors for universal digraph instances, like the `CompleteDigraph`, the `EmptyDigraph` or the *circular oriented* `GridDigraph` constructor, are readily available (see Fig. 1.3).

```

1 >>> from digraphs import GridDigraph
2 >>> grid = GridDigraph(n=5,m=5,hasMedianSplitOrientation=True)

```

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```
3 >>> grid.exportGraphViz('tutorialGrid')
4     ----- exporting a dot file for GraphViz tools -----
5     Exporting to tutorialGrid.dot
6     dot -Grankdir=BT -Tpng TutorialGrid.dot -o tutorialGrid.png
```

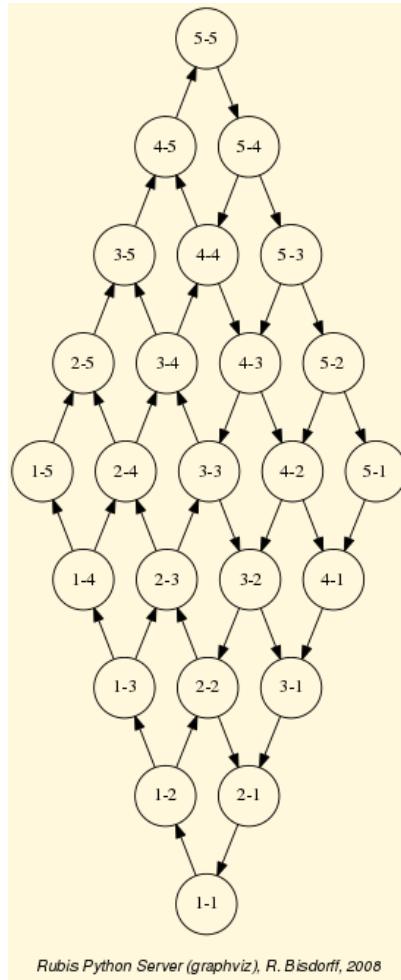


Fig. 1.3: The 5x5 grid graph median split oriented

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1.2 Working with the `digraphs` module

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Abstract: The tutorial introduces bipolar-valued digraphs, the fundamental root type of all the specialised digraphs implemented in the *Digraph3* modules. With the help of a randomly valued digraph, we illustrate some basic digraph manipulation methods, like drawing the digraph, dividing the digraph into its asymmetric and symmetric parts, separating the border from the inner part, computing associated dual, converse and codual digraphs, and operating symmetric and transitive closures

Random digraphs

We are starting this tutorial with generating a uniformly random [-1.0; +1.0]-valued digraph of order 7, denoted *rdg* and modelling, for instance, a binary relation ($x \mathcal{S} y$) defined on the set of nodes of *rdg*. For this purpose, the *Digraph3* collection contains a `randomDigraphs` module providing a specific `RandomValuationDigraph` constructor.

Listing 1.4: Random bipolar-valued digraph instance

```

1  >>> from randomDigraphs import RandomValuationDigraph
2  >>> rdg = RandomValuationDigraph(order=7)
3  >>> rdg.save('tutRandValDigraph')
4  >>> from digraphs import Digraph
5  >>> rdg = Digraph('tutRandValDigraph')
6  >>> rdg
7  *----- Digraph instance description -----*
8  Instance class      : Digraph
9  Instance name       : tutRandValDigraph
10 Digraph Order       : 7
11 Digraph Size        : 22
12 Valuation domain   : [-1.00;1.00]
13 Determinateness (%) : 75.24
14 Attributes          : ['name', 'actions', 'order',
15                           'valuationdomain', 'relation',
16                           'gamma', 'notGamma']

```

With the `save()` method (see Listing 1.4 Line 3) we may keep a backup version for future use of *rdg* which will be stored in a file called *tutRandValDigraph.py* in the current

working directory. The generic `Digraph` class constructor may restore the `rdg` object from the stored file (Line 4). We may easily inspect the content of `rdg` (Lines 5). The digraph size 22 indicates the number of positively valued arcs. The valuation domain is uniformly distributed in the interval $[-1.0; 1.0]$ and the mean absolute arc valuation is $(0.7524 \times 2) - 1.0 = 0.5048$ (Line 12).

All `Digraph` objects contain at least the list of attributes shown here: a **name** (string), a dictionary of **actions** (digraph nodes), an **order** (integer) attribute containing the number of actions, a **valuationdomain** dictionary, a double dictionary **relation** representing the adjacency table of the digraph relation, a **gamma** and a **notGamma** dictionary containing the direct neighbourhood of each action.

As mentioned previously, the `Digraph` class provides some generic `show...` methods for exploring a given `Digraph` object, like the `showShort()`, `showAll()`, `showRelationTable()` and the `showNeighborhoods()` methods.

Listing 1.5: Example of random valuation digraph

```

1  >>> rdg.showAll()
2  ----- show detail -----
3  Digraph          : tutRandValDigraph
4  ----- Actions ----*
5  ['1', '2', '3', '4', '5', '6', '7']
6  ----- Characteristic valuation domain ----*
7  {'med': Decimal('0.0'), 'hasIntegerValuation': False,
8   'min': Decimal('-1.0'), 'max': Decimal('1.0')}
9  * ---- Relation Table ----
10 r(xSy) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
11 -----|-----
12 '1'   |  0.00 -0.48  0.70  0.86  0.30  0.38  0.44
13 '2'   | -0.22  0.00 -0.38  0.50  0.80 -0.54  0.02
14 '3'   | -0.42  0.08  0.00  0.70 -0.56  0.84 -1.00
15 '4'   |  0.44 -0.40 -0.62  0.00  0.04  0.66  0.76
16 '5'   |  0.32 -0.48 -0.46  0.64  0.00 -0.22 -0.52
17 '6'   | -0.84  0.00 -0.40 -0.96 -0.18  0.00 -0.22
18 '7'   |  0.88  0.72  0.82  0.52 -0.84  0.04  0.00
19 *---- Connected Components ---*
20 1: ['1', '2', '3', '4', '5', '6', '7']
21 Neighborhoods:
22 Gamma:
23 '1': in => {'5', '7', '4'}, out => {'5', '7', '6', '3', '4'}
24 '2': in => {'7', '3'}, out => {'5', '7', '4'}
25 '3': in => {'7', '1'}, out => {'6', '2', '4'}
26 '4': in => {'5', '7', '1', '2', '3'}, out => {'5', '7', '1', '6'}
27 '5': in => {'1', '2', '4'}, out => {'1', '4'}
28 '6': in => {'7', '1', '3', '4'}, out => set()
29 '7': in => {'1', '2', '4'}, out => {'1', '2', '3', '4', '6'}
30 Not Gamma:
31 '1': in => {'6', '2', '3'}, out => {'2'}

```

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```

32 '2': in => {'5', '1', '4'}, out => {'1', '6', '3'}
33 '3': in => {'5', '6', '2', '4'}, out => {'5', '7', '1'}
34 '4': in => {'6'}, out => {'2', '3'}
35 '5': in => {'7', '6', '3'}, out => {'7', '6', '2', '3'}
36 '6': in => {'5', '2'}, out => {'5', '7', '1', '3', '4'}
37 '7': in => {'5', '6', '3'}, out => {'5'}

```

Warning

Mind that most Digraph class methods will ignore the **reflexive** links by considering that they are **indeterminate**, i.e. the characteristic value $r(xSx)$ for all action x is set to the *median*, i.e. *indeterminate* value 0.0 in this case (see Listing 1.5 Lines 12-18 and [BIS-2004a]).

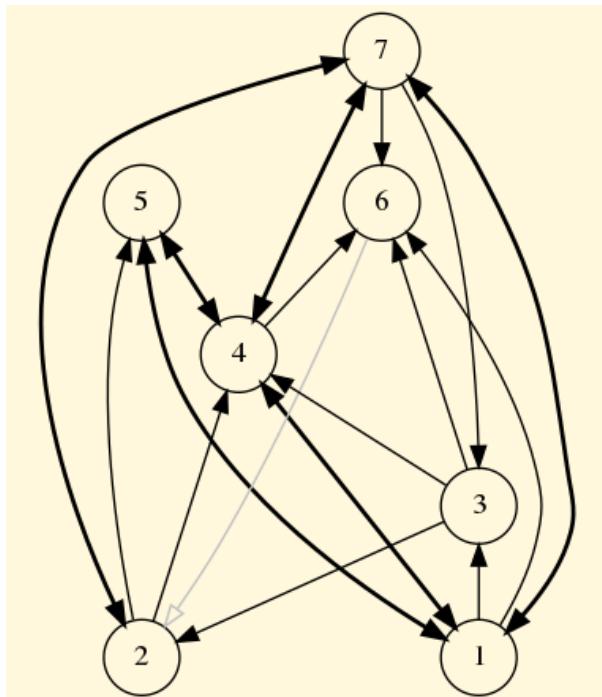
Graphviz drawings

We may even get a better insight into the Digraph object `rdg` by looking at a graphviz (<https://graphviz.org/>) drawing^{[Page 7, 1](#)}.

```

1 >>> rdg.exportGraphViz('tutRandValDigraph')
2     ----- exporting a dot file for GraphViz tools -----
3     Exporting to tutRandValDigraph.dot
4     dot -Grankdir=BT -Tpng tutRandValDigraph.dot -o tutRandValDigraph.png

```



Rubis Python Server (graphviz), R. Bisendorff, 2008

Fig. 1.4: The tutorial random valuation digraph

Double links are drawn in bold black with an arrowhead at each end, whereas single asymmetrical links are drawn in black with an arrowhead showing the direction of the link. Notice the indeterminate relational situation ($r(6 \ S 2) = 0.00$) observed between nodes ‘6’ and ‘2’. The corresponding link is marked in gray with an open arrowhead in the drawing (see Fig. 1.4).

Asymmetrical and symmetrical parts

We may now extract both the *symmetrical* as well as the *asymmetrical* part of digraph *dg* with the help of two corresponding constructors (see Fig. 1.5).

```

1 >>> from digraphs import AsymmetricPartialDigraph,
2 ...                               SymmetricPartialDigraph
3
4 >>> asymDg = AsymmetricPartialDigraph(rdg)
5 >>> asymDg.exportGraphViz()
6 >>> symDg = SymmetricPartialDigraph(rdg)
7 >>> symDg.exportGraphViz()
```

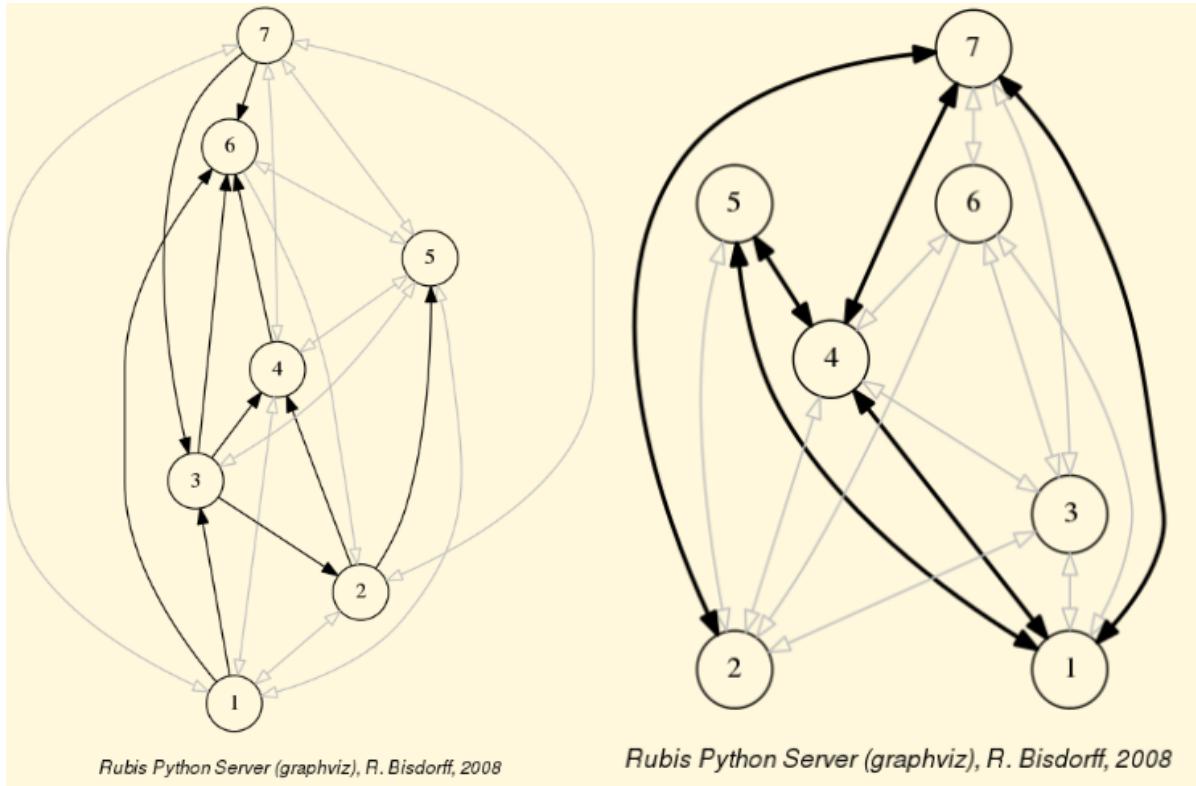


Fig. 1.5: Asymmetrical and symmetrical parts of the tutorial random valuation digraph

Note

The constructor of the partial objects *asymDg* and *symDg* puts to the indeterminate characteristic value all *not-asymmetrical*, respectively *not-symmetrical* links between nodes (see Fig. 1.5).

Here below, for illustration the source code of the *relation* constructor of the *AsymmetricPartialDigraph* class.

```

1 def _constructRelation(self):
2     actions = self.actions
3     Min = self.valuationdomain['min']
4     Max = self.valuationdomain['max']
5     Med = self.valuationdomain['med']
6     relationIn = self.relation
7     relationOut = {}
8     for a in actions:
9         relationOut[a] = {}
10        for b in actions:
11            if a != b:
12                if relationIn[a][b] >= Med and relationIn[b][a] <= Med:
13                    relationOut[a][b] = relationIn[a][b]
14                elif relationIn[a][b] <= Med and relationIn[b][a] >= Med:
15                    relationOut[a][b] = relationIn[a][b]
16                else:
17                    relationOut[a][b] = Med
18            else:
19                relationOut[a][b] = Med
20
return relationOut

```

Border and inner parts

We may also extract the border -the part of a digraph induced by the union of its initial and terminal prekernels (see tutorial Kernel-Tutorial-label)- as well as, the inner part -the *complement* of the border- with the help of two corresponding class constructors: *GraphBorder* and *GraphInner* (see Listing 1.6).

Let us illustrate these parts on a linear ordering obtained from the tutorial random valuation digraph *rdg* with the *NetFlows ranking rule* (page 91) (see Listing 1.6 Line 2-3).

Listing 1.6: Border and inner part of a linear order

```

1 >>> from digraphs import GraphBorder, GraphInner
2 >>> from linearOrders import NetFlowsOrder
3 >>> nf = NetFlowsOrder(rdg)
4 >>> nf.netFlowsOrder
5   ['6', '4', '5', '3', '2', '1', '7']
6 >>> bnf = GraphBorder(nf)
7 >>> bnf.exportGraphViz(worstChoice=['6'], bestChoice=['7'])
8 >>> inf = GraphInner(nf)
9 >>> inf.exportGraphViz(worstChoice=['6'], bestChoice=['7'])

```



Fig. 1.6: *Border* and *inner* part of a linear order oriented by *terminal* and *initial* kernels

We may orient the graphviz drawings in Fig. 1.6 with the terminal node 6 (*worstChoice* parameter) and initial node 7 (*bestChoice* parameter), see Listing 1.6 Lines 7 and 9).

Note

The constructor of the partial digraphs *bnf* and *inf* (see Listing 1.6 Lines 3 and 6) puts to the *indeterminate* characteristic value all links *not* in the *border*, respectively *not* in the *inner* part (see Fig. 1.7).

Being much *denser* than a linear order, the actual inner part of our tutorial random valuation digraph dg is reduced to a single arc between nodes 3 and 4 (see Fig. 1.7).



Fig. 1.7: Border and inner part of the tutorial random valuation digraph rdg

Indeed, a *complete* digraph on the limit has no inner part –privacy!– at all as all its arcs appear in the border. Notice that *empty* and *indeterminate* digraphs admit both, an empty border and an empty inner part. When in general a given digraph –like an oriented chordless cycle– does not admit any initial or terminal prekernels, its border part will be empty and its inner part will contain all its arcs. The digraph’s relation is *closed* on itself and shows indeed no laterality⁶⁵.

Fusion by epistemic disjunction

We may recover object rdg from both partial objects $asymDg$ and $symDg$, or as well from the border bg and the inner part ig , with a **bipolar fusion** constructor, also called **epistemic disjunction**, available via the `FusionDigraph` class (see Listing 1.4 Lines 12-21).

Listing 1.7: Epistemic fusion of partial digraphs

```

1 >>> from digraphs import FusionDigraph
2 >>> fusDg = FusionDigraph(asymDg,symDg,operator='o-max')
3 >>> # fusDg = FusionDigraph(bg,ig,operator='o-max')
4 >>> fusDg.showRelationTable()
5 * ---- Relation Table ----
6 r(xSy) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
7 -----|-----
```

(continues on next page)

⁶⁵ An example of a borderless `RandomOutrankingValuationDigraph` instance may be found in the `examples` directory of the `Digraphs3` resources under the name `borderlessROV9S25.py`.

(continued from previous page)

8	'1'		0.00	-0.48	0.70	0.86	0.30	0.38	0.44
9	'2'		-0.22	0.00	-0.38	0.50	0.80	-0.54	0.02
10	'3'		-0.42	0.08	0.00	0.70	-0.56	0.84	-1.00
11	'4'		0.44	-0.40	-0.62	0.00	0.04	0.66	0.76
12	'5'		0.32	-0.48	-0.46	0.64	0.00	-0.22	-0.52
13	'6'		-0.84	0.00	-0.40	-0.96	-0.18	0.00	-0.22
14	'7'		0.88	0.72	0.82	0.52	-0.84	0.04	0.00

The *epistemic fusion* (page 17) operator **o-max** (see Listing 1.7 Line 2) works as follows.

Let r and r' characterise two bipolar-valued epistemic situations.

- $\text{o-max}(r, r') = \max(r, r')$ when both r and r' are more or less valid or indeterminate;
- $\text{o-max}(r, r') = \min(r, r')$ when both r and r' are more or less invalid or indeterminate;
- $\text{o-max}(r, r') = \text{indeterminate}$ otherwise.

Dual, converse and codual digraphs

We may as readily compute the **dual** (negated relation¹⁴), the **converse** (transposed relation) and the **codual** (transposed and negated relation) of the digraph instance rdg .

```

1 >>> from digraphs import DualDigraph, ConverseDigraph, CoDualDigraph
2 >>> ddg = DualDigraph(rdg)
3 >>> ddg.showRelationTable()
4 -r(xSy) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
5 -----|-----
6 '1' | 0.00  0.48 -0.70 -0.86 -0.30 -0.38 -0.44
7 '2' | 0.22  0.00  0.38 -0.50  0.80  0.54 -0.02
8 '3' | 0.42  0.08  0.00 -0.70  0.56 -0.84  1.00
9 '4' | -0.44 0.40  0.62  0.00 -0.04 -0.66 -0.76
10 '5' | -0.32 0.48  0.46 -0.64  0.00  0.22  0.52
11 '6' | 0.84  0.00  0.40  0.96  0.18  0.00  0.22
12 '7' | 0.88 -0.72 -0.82 -0.52  0.84 -0.04  0.00
13 >>> cdg = ConverseDigraph(rdg)
14 >>> cdg.showRelationTable()
15 * ----- Relation Table -----
16 r(ySx) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
17 -----|-----
18 '1' | 0.00 -0.22 -0.42  0.44  0.32 -0.84  0.88
19 '2' | -0.48 0.00  0.08 -0.40 -0.48  0.00  0.72
20 '3' | 0.70 -0.38  0.00 -0.62 -0.46 -0.40  0.82

```

(continues on next page)

¹⁴ Not to be confused with the *dual graph* of a plane graph g that has a vertex for each face of g . Here we mean the *less than* (strict converse) relation corresponding to a *greater or equal* relation, or the *less than or equal* relation corresponding to a (strict) *better than* relation.

(continued from previous page)

```

21   '4' |  0.86  0.50  0.70  0.00  0.64 -0.96  0.52
22   '5' |  0.30  0.80 -0.56  0.04  0.00 -0.18 -0.84
23   '6' |  0.38 -0.54  0.84  0.66 -0.22  0.00  0.04
24   '7' |  0.44  0.02 -1.00  0.76 -0.52 -0.22  0.00
25 >>> cddg = CoDualDigraph(rdg)
26 >>> cddg.showRelationTable()
27 * ---- Relation Table ----
28 -r(ySx) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
29   -----|-----
30   '1' |  0.00  0.22  0.42 -0.44 -0.32  0.84 -0.88
31   '2' |  0.48  0.00 -0.08  0.40  0.48  0.00 -0.72
32   '3' | -0.70  0.38  0.00  0.62  0.46  0.40 -0.82
33   '4' | -0.86 -0.50 -0.70  0.00 -0.64  0.96 -0.52
34   '5' | -0.30 -0.80  0.56 -0.04  0.00  0.18  0.84
35   '6' | -0.38  0.54 -0.84 -0.66  0.22  0.00 -0.04
36   '7' | -0.44 -0.02  1.00 -0.76  0.52  0.22  0.00

```

Computing the *dual*, respectively the *converse*, may also be done with prefixing the `__neg__` (-) or the `__invert__` (~) operator. The *codual* of a Digraph object may, hence, as well be computed with a **composition** (in either order) of both operations.

Listing 1.8: Computing the *dual*, the *converse* and the *codual* of a digraph

```

1 >>> ddg = -rdg    # dual of rdg
2 >>> cdg = ~rdg    # converse of rdg
3 >>> cddg = ~(-rdg) # = -(~rdg) codual of rdg
4 >>> (-(~rdg)).showRelationTable()
5 * ---- Relation Table ----
6 -r(ySx) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
7   -----|-----
8   '1' |  0.00  0.22  0.42 -0.44 -0.32  0.84 -0.88
9   '2' |  0.48  0.00 -0.08  0.40  0.48  0.00 -0.72
10  '3' | -0.70  0.38  0.00  0.62  0.46  0.40 -0.82
11  '4' | -0.86 -0.50 -0.70  0.00 -0.64  0.96 -0.52
12  '5' | -0.30 -0.80  0.56 -0.04  0.00  0.18  0.84
13  '6' | -0.38  0.54 -0.84 -0.66  0.22  0.00 -0.04
14  '7' | -0.44 -0.02  1.00 -0.76  0.52  0.22  0.00

```

Symmetric and transitive closures

Symmetric and transitive closures, by default in-location constructors, are also available (see Fig. 1.8). Note that it is a good idea, before going ahead with these in-site operations, who irreversibly modify the original `rdg` object, to previously make a backup version of `rdg`. The simplest storage method, always provided by the generic `save()`, writes out in a named file the python content of the Digraph object in string representation.

Listing 1.9: Symmetric and transitive in-site closures

```

1 >>> rdg.save('tutRandValDigraph')
2 >>> rdg.closeSymmetric(InSite=True)
3 >>> rdg.closeTransitive(InSite=True)
4 >>> rdg.exportGraphViz('strongComponents')

```



Fig. 1.8: Symmetric and transitive in-site closures

The `closeSymmetric()` method (see Listing 1.9 Line 2), of complexity $\mathcal{O}(n^2)$ where n denotes the digraph's order, changes, on the one hand, all single pairwise links it may detect into double links by operating a disjunction of the pairwise relations. On the other hand, the `closeTransitive()` method (see Listing 1.9 Line 3), implements the *Roy-Warshall* transitive closure algorithm of complexity $\mathcal{O}(n^3)$. (17)

Note

The same `closeTransitive()` method with a `Reverse = True` flag may be readily used for eliminating all transitive arcs from a transitive digraph instance. We make usage of this feature when drawing *Hasse diagrams* of `TransitiveDigraph` objects.

¹⁷ Roy, B. *Transitivité et connexité*. C. R. Acad. Sci. Paris 249, 216-218, 1959. Marshall, S. A *Theorem on Boolean Matrices*. J. ACM 9, 11-12, 1962.

Strong components

As the original digraph *rdg* was connected (see above the result of the `showShort()` command), both the symmetric and the transitive closures operated together, will necessarily produce a single strong component, i.e. a **complete** digraph. We may sometimes wish to collapse all strong components in a given digraph and construct the so *collapsed* digraph. Using the `StrongComponentsCollapsedDigraph` constructor here will render a single hyper-node gathering all the original nodes (see Line 7 below).

```
1  >>> from digraphs import StrongComponentsCollapsedDigraph
2  >>> sc = StrongComponentsCollapsedDigraph(dg)
3  >>> sc.showAll()
4  ----- show detail -----
5  Digraph           : tutRandValDigraph_Scc
6  ----- Actions -----
7  ['_7_1_2_6_5_3_4_']
8  * ---- Relation Table ----
9  S      |  'Scc_1'
10   -----|-----
11 'Scc_1' |  0.00
12 short       content
13 Scc_1       _7_1_2_6_5_3_4_
14 Neighborhoods:
15   Gamma     :
16 'frozenset({'7', '1', '2', '6', '5', '3', '4'})': in => set(), out => set()
17   Not Gamma :
18 'frozenset({'7', '1', '2', '6', '5', '3', '4'})': in => set(), out => set()
```

CSV storage

Sometimes it is required to exchange the graph valuation data in CSV format with a statistical package like [R](#) (<https://www.r-project.org/>). For this purpose it is possible to export the digraph data into a CSV file. The valuation domain is hereby normalized by default to the range [-1,1] and the diagonal put by default to the minimal value -1.

```
1  >>> rdg = Digraph('tutRandValDigraph')
2  >>> rdg.saveCSV('tutRandValDigraph')
3  # content of file tutRandValDigraph.csv
4  "d","1","2","3","4","5","6","7"
5  "1",-1.0,0.48,-0.7,-0.86,-0.3,-0.38,-0.44
6  "2",0.22,-1.0,0.38,-0.5,-0.8,0.54,-0.02
7  "3",0.42,-0.08,-1.0,-0.7,0.56,-0.84,1.0
8  "4",-0.44,0.4,0.62,-1.0,-0.04,-0.66,-0.76
9  "5",-0.32,0.48,0.46,-0.64,-1.0,0.22,0.52
10 "6",0.84,0.0,0.4,0.96,0.18,-1.0,0.22
11 "7",-0.88,-0.72,-0.82,-0.52,0.84,-0.04,-1.0
```

It is possible to reload a Digraph instance from its previously saved CSV file content.

```

1 >>> from digraphs import CSVDigraph
2 >>> rdgcsv = CSVDigraph('tutRandValDigraph')
3 >>> rdgcsv.showRelationTable(ReflexiveTerms=False)
4 * ---- Relation Table ----
5 r(xSy) | '1'   '2'   '3'   '4'   '5'   '6'   '7'
6 -----|-----
7 '1'    | -0.48  0.70  0.86  0.30  0.38  0.44
8 '2'    | -0.22  -0.38  0.50  0.80 -0.54  0.02
9 '3'    | -0.42  0.08   -    0.70 -0.56  0.84 -1.00
10 '4'   |  0.44 -0.40 -0.62   -   0.04  0.66  0.76
11 '5'   |  0.32 -0.48 -0.46  0.64   - -0.22 -0.52
12 '6'   | -0.84  0.00 -0.40 -0.96 -0.18   - -0.22
13 '7'   |  0.88  0.72  0.82  0.52 -0.84  0.04   -

```

It is as well possible to show a colored version of the valued relation table in a system browser window tab (see Fig. 1.9).

```

1 >>> rdgcsv.showHTMLRelationTable(tableTitle="Tutorial random digraph")

```

Tutorial random digraph

r(x S y)	1	2	3	4	5	6	7
1	0.00	-0.48	0.70	0.86	0.30	0.38	0.44
2	-0.22	0.00	-0.38	0.50	0.80	-0.54	0.02
3	-0.42	0.08	0.00	0.70	-0.56	0.84	-1.00
4	0.44	-0.40	-0.62	0.00	0.04	0.66	0.76
5	0.32	-0.48	-0.46	0.64	0.00	-0.22	-0.52
6	-0.84	0.00	-0.40	-0.96	-0.18	0.00	-0.22
7	0.88	0.72	0.82	0.52	-0.84	0.04	0.00

Fig. 1.9: The valued relation table shown in a browser window

Positive arcs are shown in *green* and negative arcs in *red*. Indeterminate -zero-valued-links, like the reflexive diagonal ones or the link between node 6 and node 2, are shown in *gray*.

Complete, empty and indeterminate digraphs

Let us finally mention some special universal classes of digraphs that are readily available in the `digraphs` module, like the `CompleteDigraph`, the `EmptyDigraph` and the `IndeterminateDigraph` classes, which put all characteristic values respectively to the *maximum*, the *minimum* or the median *indeterminate* characteristic value.

Listing 1.10: Complete, empty and indeterminate di-graphs

```

1  >>> from digraphs import CompleteDigraph,EmptyDigraph,
2      IndeterminateDigraph
3  >>> e = EmptyDigraph(order=5)
4  >>> e.showRelationTable()
5  * ---- Relation Table ----
6  S | '1'   '2'   '3'   '4'   '5'
7  - +-----+
8  '1' | -1.00 -1.00 -1.00 -1.00 -1.00
9  '2' | -1.00 -1.00 -1.00 -1.00 -1.00
10 '3' | -1.00 -1.00 -1.00 -1.00 -1.00
11 '4' | -1.00 -1.00 -1.00 -1.00 -1.00
12 '5' | -1.00 -1.00 -1.00 -1.00 -1.00
13 >>> e.showNeighborhoods()
14 Neighborhoods:
15     Gamma :
16     '1': in => set(), out => set()
17     '2': in => set(), out => set()
18     '5': in => set(), out => set()
19     '3': in => set(), out => set()
20     '4': in => set(), out => set()
21     Not Gamma :
22     '1': in => {'2', '4', '5', '3'}, out => {'2', '4', '5', '3'}
23     '2': in => {'1', '4', '5', '3'}, out => {'1', '4', '5', '3'}
24     '5': in => {'1', '2', '4', '3'}, out => {'1', '2', '4', '3'}
25     '3': in => {'1', '2', '4', '5'}, out => {'1', '2', '4', '5'}
26     '4': in => {'1', '2', '5', '3'}, out => {'1', '2', '5', '3'}
27 >>> i = IndeterminateDigraph()
28 * ---- Relation Table ----
29     S | '1'   '2'   '3'   '4'   '5'
30     - +-----+
31     '1' | 0.00  0.00  0.00  0.00  0.00
32     '2' | 0.00  0.00  0.00  0.00  0.00
33     '3' | 0.00  0.00  0.00  0.00  0.00
34     '4' | 0.00  0.00  0.00  0.00  0.00
35     '5' | 0.00  0.00  0.00  0.00  0.00
36 >>> i.showNeighborhoods()
37 Neighborhoods:
38     Gamma :
39     '1': in => set(), out => set()
40     '2': in => set(), out => set()
41     '5': in => set(), out => set()
42     '3': in => set(), out => set()
43     '4': in => set(), out => set()
44     Not Gamma :
```

(continues on next page)

```

44 '1': in => set(), out => set()
45 '2': in => set(), out => set()
46 '5': in => set(), out => set()
47 '3': in => set(), out => set()
48 '4': in => set(), out => set()

```

Note

Mind the subtle difference between the neighborhoods of an **empty** and the neighborhoods of an **indeterminate** digraph instance. In the first kind, the neighborhoods are known to be completely *empty* (see Listing 1.10 Lines 20-25) whereas, in the latter, *nothing is known* about the actual neighborhoods of the nodes (see Listing 1.10 Lines 43-48). These two cases illustrate why in the case of **bipolar-valued** digraphs, we may need both a *gamma* and a *notGamma* attribute.

Historical notes

It was *Denis Bouyssou* who first suggested us end of the nineties, when we started to work in Prolog on the computation of fuzzy digraph kernels with finite domain constraint solvers, that the 50% criteria significance majority is a very special value that has to be carefully taken into account. The converging solution vectors of the fixpoint kernel equations furthermore confirmed this special status of the 50% majority (see Computing bipolar-valued kernel membership characteristic vectors). These early insights led to the seminal articles on bipolar-valued epistemic logic where we introduced split truth/falseness semantics for a multi-valued logical processing of fuzzy preference modelling ([BIS-2000] and [BIS-2004a]). The characteristic valuation domain remained however the classical fuzzy [0.0;1.0] valuation domain.

It is only in 2004, when we succeeded in assessing the stability of the outranking digraph when solely ordinal criteria significance weights are given, that it became clear and evident for us that the characteristic valuation domain had to be shifted to a [-1.0;+1.0]-valued domain (see Ordinal correlation equals bipolar-valued relational equivalence and [BIS-2004b]). In this bipolar valuation, the 50% majority threshold corresponds now to the median 0.0 value, characterising with the correct zero value an epistemic indeterminateness -no knowledge- situation. Furthermore, identifying truth and falseness directly by the sign of the characteristic value revealed itself to be very efficient not only from a computational point of view, but also from scientific and semiotic perspectives. A positive (resp. negative) characteristic value now attest a logically valid (resp. invalid) statement and a negative affirmation now means a positive refutation and vice versa. Furthermore, the median zero value gives way to efficiently handling partial objects -like the border or the assymetric part of a digraph- and, even more important from a practical decision making point of view, any missing data.

The bipolar [-1.0;+1.0]-valued characteristic domain opened so the way to important new operations and concepts, like the disjunctive epistemic fusion operation seen before which confers the outranking digraph a logically sound and epistemically correct definition ([BIS-2013]). *Kendall's* ordinal correlation index could be extended to a bipolar-valued

relational equivalence index between digraphs (see Ordinal correlation equals bipolar-valued relational equivalence and [BIS-2012]). Making usage of the bipolar-valued *Gaussian* error function (*erf*) naturally led to defining a bipolar-valued likelihood function, where a positive, resp. negative, value gives the likelihood of an affirmation, resp. a refutation.

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1.3 Working with the `outrankingDigraphs` module

- *Outranking digraph model* (page 25)
- *The bipolar-valued outranking digraph* (page 28)
- *Pairwise comparisons* (page 29)
- *Recoding the digraph valuation* (page 30)
- *The strict outranking digraph* (page 30)
- *Historical Notes* (page 32)

Abstract: In this chapter, we introduce the main formal object of this book, namely the bipolar-valued outranking digraph. With a randomly generated multiple-criteria performance tableau, we construct the corresponding bipolar-valued outranking relation from pairwise comparisons. The resulting bipolar-valued outranking characteristics may be recoded. Finally, the codual outranking digraph gives us the associated strict outranking relation.

Outranking digraph model

“The rule for the combination of independent concurrent arguments takes a very simple form when expressed in terms of the intensity of belief ... It is this: Take the sum of all the feelings of belief which would be produced separately by all the arguments pro, subtract from that the similar sum for arguments con, and the remainder is the feeling of belief which ought to have the whole. This is a proceeding which men often resort to, under the name of balancing reasons.” – C.S. Peirce, The probability of induction (1878)

In this `Digraph3` module, the `BipolarOutrankingDigraph` class from the `outrankingDigraphs` module provides our standard **outranking digraph** constructor. Such an instance represents a **hybrid** object of both, the `PerformanceTableau` type and the `OutrankingDigraph` type. A given object consists hence in:

1. an ordered dictionary of decision **actions** describing the potential decision actions or alternatives with ‘name’ and ‘comment’ attributes,

2. a possibly empty ordered dictionary of decision **objectives** with ‘name’ and ‘comment’ attributes, describing the multiple preference dimensions involved in the decision problem,
3. a dictionary of performance **criteria** describing *preferentially independent* and *non-redundant* decimal-valued functions used for measuring the performance of each potential decision action with respect to a decision objective,
4. a double dictionary **evaluation** gathering performance grades for each decision action or alternative on each criterion function.
5. the digraph **valuationdomain**, a dictionary with three entries: the *minimum* (-1.0, certainly outranked), the *median* (0.0, indeterminate) and the *maximum* characteristic value (+1.0, certainly outranking),
6. the outranking **relation** : a double dictionary defined on the Cartesian product of the set of decision alternatives capturing the credibility of the pairwise *outranking situation* computed on the basis of the performance differences observed between couples of decision alternatives on the given family of criteria functions.

Let us construct, for instance, a random bipolar-valued outranking digraph with seven decision actions denotes a_1, a_2, \dots, a_7 . We need therefore to first generate a corresponding random performance tableaux (see below).

```

1  >>> from outrankingDigraphs import *
2  >>> pt = RandomPerformanceTableau(numberOfActions=7,
3  ...                               seed=100)
4
5  >>> pt
6  *----- PerformanceTableau instance description -----*
7  Instance class      : RandomPerformanceTableau
8  Seed                : 100
9  Instance name       : randomperftab
10 # Actions           : 7
11 # Criteria          : 7
12 NaN proportion (%) : 6.1
13 >>> pt.showActions()
14 *----- show digraphs actions -----*
15 key: a1
16     name:      action #1
17     comment:   RandomPerformanceTableau() generated.
18 key: a2
19     name:      action #2
20     comment:   RandomPerformanceTableau() generated.
21 ...
22 ...
23 key: a7
24     name:      action #7
25     comment:   RandomPerformanceTableau() generated.

```

In this example we consider furthermore a family of seven **equisignificant cardinal**

criteria functions g_1, g_2, \dots, g_7 , measuring the performance of each alternative on a rational scale from 0.0 (worst) to 100.00 (best). In order to capture the grading procedure's potential uncertainty and imprecision, each criterion function g_1 to g_7 admits three performance **discrimination thresholds** of 2.5, 5.0 and 80 pts for warranting respectively any indifference, preference or considerable performance difference situation.

```

1  >>> pt.showCriteria()
2  ----- criteria -----
3  g1 'RandomPerformanceTableau() instance'
4    Scale = [0.0, 100.0]
5    Weight = 1.0
6    Threshold ind : 2.50 + 0.00x ; percentile: 4.76
7    Threshold pref : 5.00 + 0.00x ; percentile: 9.52
8    Threshold veto : 80.00 + 0.00x ; percentile: 95.24
9  g2 'RandomPerformanceTableau() instance'
10   Scale = [0.0, 100.0]
11   Weight = 1.0
12   Threshold ind : 2.50 + 0.00x ; percentile: 6.67
13   Threshold pref : 5.00 + 0.00x ; percentile: 6.67
14   Threshold veto : 80.00 + 0.00x ; percentile: 100.00
15   ...
16   ...
17  g7 'RandomPerformanceTableau() instance'
18   Scale = [0.0, 100.0]
19   Weight = 1.0
20   Threshold ind : 2.50 + 0.00x ; percentile: 0.00
21   Threshold pref : 5.00 + 0.00x ; percentile: 4.76
22   Threshold veto : 80.00 + 0.00x ; percentile: 100.00

```

On criteria function g_1 (see Lines 6-8 above) we observe, for instance, about 5% of **indifference**, about 90% of **preference** and about 5% of **considerable** performance difference situations. The individual performance evaluation of all decision alternative on each criterion are gathered in a *performance tableau*.

```

1  >>> pt.showPerformanceTableau(Transposed=True,ndigits=1)
2  ----- performance tableau -----
3  criteria | weights | 'a1'  'a2'  'a3'  'a4'  'a5'  'a6'  'a7'
4  -----|-----|-----
5  'g1'   | 1      | 15.2  44.5  57.9  58.0  24.2  29.1  96.6
6  'g2'   | 1      | 82.3  43.9  NA     35.8  29.1  34.8  62.2
7  'g3'   | 1      | 44.2  19.1  27.7  41.5  22.4  21.5  56.9
8  'g4'   | 1      | 46.4  16.2  21.5  51.2  77.0  39.4  32.1
9  'g5'   | 1      | 47.7  14.8  79.7  67.5  NA     90.7  80.2
10  'g6'  | 1      | 69.6  45.5  22.0  33.8  31.8  NA     48.8
11  'g7'  | 1      | 82.9  41.7  12.8  21.9  75.7  15.4  6.0

```

It is noteworthy to mention the three **missing data** (*NA*) cases: action a_3 is missing, for instance, a grade on criterion g_2 (see Line 6 above).

The bipolar-valued outranking digraph

Given the previous random performance tableau pt , the `BipolarOutrankingDigraph` constructor computes the corresponding **bipolar-valued outranking digraph**.

Listing 1.11: Example of random bipolar-valued outranking digraph

```

1 >>> odg = BipolarOutrankingDigraph(pt)
2 >>> odg
3 *----- Object instance description -----*
4 Instance class      : BipolarOutrankingDigraph
5 Instance name        : rel_randomperftab
6 # Actions            : 7
7 # Criteria           : 7
8 Size                 : 20
9 Determinateness (%) : 63.27
10 Valuation domain    : [-1.00;1.00]
11 Attributes          : [
12   'name', 'actions',
13   'criteria', 'evaluation', 'NA',
14   'valuationdomain', 'relation',
15   'order', 'gamma', 'notGamma', ...
16 ]

```

The resulting digraph contains 20 positive (valid) outranking relations. And, the mean majority criteria significance support of all the pairwise outranking situations is 63.3% (see Listing 1.11 Lines 8-9). We may inspect the complete $[-1.0, +1.0]$ -valued adjacency table as follows.

```

1 >>> odg.showRelationTable()
2 * ---- Relation Table -----
3 r(x,y)| 'a1'   'a2'   'a3'   'a4'   'a5'   'a6'   'a7'
4 -----|-----
5 'a1' | +1.00  +0.71  +0.29  +0.29  +0.29  +0.29  +0.00
6 'a2' | -0.71  +1.00  -0.29  -0.14  +0.14  +0.29  -0.57
7 'a3' | -0.29  +0.29  +1.00  -0.29  -0.14  +0.00  -0.29
8 'a4' | +0.00  +0.14  +0.57  +1.00  +0.29  +0.57  -0.43
9 'a5' | -0.29  +0.00  +0.14  +0.00  +1.00  +0.29  -0.29
10 'a6' | -0.29  +0.00  +0.14  -0.29  +0.14  +1.00  +0.00
11 'a7' | +0.00  +0.71  +0.57  +0.43  +0.29  +0.00  +1.00
12 Valuation domain: [-1.0; 1.0]

```

Considering the given performance tableau pt , the `BipolarOutrankingDigraph` class constructor computes the characteristic value $r(x \succsim y)$ of a **pairwise outranking** relation “ $x \succsim y$ ” (see [BIS-2013], [ADT-L7]) in a default *normalised valuation domain* $[-1.0, +1.0]$ with the *median value* 0.0 acting as **indeterminate** characteristic value. The semantics of $r(x \succsim y)$ are the following.

1. When $r(x \succsim y) > 0.0$, it is more *True* than *False* that x **outranks** y , i.e. alter-

native x is at least as well performing than alternative y on a weighted majority of criteria **and** there is no considerable negative performance difference observed in disfavour of x ,

2. When $r(x \succsim y) < 0.0$, it is more *False* than *True* that x **outranks** y , i.e. alternative x is **not** at least as well performing on a weighted majority of criteria than alternative y **and** there is no considerable positive performance difference observed in favour of x ,
3. When $r(x \succsim y) = 0.0$, it is **indeterminate** whether x outranks y or not.

Pairwise comparisons

From above given semantics, we may consider (see Line 5 above) that $a1$ outranks $a2$ ($r(a_1 \succsim a_2) > 0.0$), but not $a7$ ($r(a_1 \succsim a_7) = 0.0$). In order to comprehend the characteristic values shown in the relation table above, we may furthermore inspect the details of the pairwise multiple criteria comparison between alternatives $a1$ and $a2$.

```

1  >>> odg.showPairwiseComparison('a1', 'a2')
2  *----- pairwise comparison -----*
3  Comparing actions : (a1, a2)
4  crit. wght. g(x) g(y) diff | ind pref r()
5  -----
6  g1  1.00  15.17  44.51 -29.34 | 2.50  5.00 -1.00
7  g2  1.00  82.29  43.90 +38.39 | 2.50  5.00 +1.00
8  g3  1.00  44.23  19.10 +25.13 | 2.50  5.00 +1.00
9  g4  1.00  46.37  16.22 +30.15 | 2.50  5.00 +1.00
10 g5  1.00  47.67  14.81 +32.86 | 2.50  5.00 +1.00
11 g6  1.00  69.62  45.49 +24.13 | 2.50  5.00 +1.00
12 g7  1.00  82.88  41.66 +41.22 | 2.50  5.00 +1.00
13 -----
14 Valuation in range: -7.00 to +7.00; r(x,y): +5/7 = +0.71

```

The outranking characteristic value $r(a_1 \succsim a_2)$ represents the **majority margin** resulting from the difference between the weights of the criteria in favor and the weights of the criteria in disfavor of the statement that alternative $a1$ is at least as well performing as alternative $a2$. No considerable performance difference being observed above, no outranking polarisation is triggered in this pairwise comparison. Such a situation is, however, observed for instance when we pairwise compare the performances of alternatives $a1$ and $a7$.

```

1  >>> odg.showPairwiseComparison('a1', 'a7')
2  *----- pairwise comparison -----*
3  Comparing actions : (a1, a7)
4  crit. wght. g(x) g(y) diff | ind pref r() | v veto
5  -----
6  g1  1.00  15.17  96.58 -81.41 | 2.50  5.00 -1.00 | 80.00 -1.00
7  g2  1.00  82.29  62.22 +20.07 | 2.50  5.00 +1.00 |
8  g3  1.00  44.23  56.90 -12.67 | 2.50  5.00 -1.00 |

```

(continues on next page)

(continued from previous page)

9	g4	1.00	46.37	32.06	+14.31		2.50	5.00	+1.00	
10	g5	1.00	47.67	80.16	-32.49		2.50	5.00	-1.00	
11	g6	1.00	69.62	48.80	+20.82		2.50	5.00	+1.00	
12	g7	1.00	82.88	6.05	+76.83		2.50	5.00	+1.00	

14	Valuation in range: -7.00 to +7.00; $r(x,y) = +1/7 \Rightarrow 0.0$									

This time, we observe a 57.1% majority of criteria significance $[(1/7 + 1)/2 = 0.571]$ warranting an *as well as performing* situation. Yet, we also observe a considerable negative performance difference on criterion *g1* (see first row in the relation table above). Both contradictory facts trigger eventually an **indeterminate** outranking situation [BIS-2013].

Recoding the digraph valuation

All outranking digraphs, being of root type `Digraph`, inherit the methods available under this latter class. The characteristic valuation domain of a digraph may, for instance, be recoded with the `recodeValutaion()` method below to the *integer* range $[-7,+7]$, i.e. plus or minus the global significance of the family of criteria considered in this example instance.

```

1 >>> odg.recodeValuation(-7,+7)
2 >>> odg.valuationdomain['hasIntegerValuation'] = True
3 >>> Digraph.showRelationTable(odg,ReflexiveTerms=True)
4 * ---- Relation Table ----
5   r(x,y) | 'a1'  'a2'  'a3'  'a4'  'a5'  'a6'  'a7'
6   -----|-----
7   'a1'  | 0     +5    +2    +2    +2    +2    0
8   'a2'  | -5    0     -1    -1    +1    +2    -4
9   'a3'  | -1    +2    0     -1    -1    0     -1
10  'a4'  | 0     +1    +4    0     +2    +4    -3
11  'a5'  | -1    0     +1    0     0     +2    -1
12  'a6'  | -1    0     +1    -1    +1    0     0
13  'a7'  | 0     +5    +4    +3    +2    0     0
14 Valuation domain: [-7;+7]

```

Warning

Notice that the reflexive self comparison characteristic $r(x \succsim x)$ is set above by default to the median indeterminate valuation value 0; the reflexive terms of binary relation being generally ignored in most of the *Digraph3* resources.

The strict outranking digraph

Bipolar-valued outranking digraphs are **strongly complete**, i.e. *complete* from a *relational* as well as from an *epistemic* perspective:

$$r(x \succsim y) + r(y \succsim x) \geq 0.0.$$

They furthermore verify the **coduality** principle: the **converse** (the *inverse* \sim) of the **dual**^{Page 18, 14} (the *negation* -) correspond to their asymmetrical **strict outranking** part:

$$\sim (-r(y \succsim x)) = \sim (r(y \not\succsim x)) = r(x \succsim y).$$

From both properties follows straightway that codual, i.e. *strict*, outranking digraphs are **strongly asymmetrical**:

$$r(x \succsim y) + r(y \succsim x) \leq 0.0$$

See the advanced topic on characterizing bipolar-valued outranking digraphs, [BIS-2013], [ADT-L7].

We may visualize the **codual** outranking digraph *cdodg* with a graphviz drawing^{Page 7, 1}.

```

1 >>> cdodg = ~(-odg) # == -(~odg) == codual transform
2 >>> cdodg.exportGraphViz('codual0dg')
3 *---- exporting a dot file for GraphViz tools -----
4 Exporting to codual0dg.dot
5 dot -Grankdir=BT -Tpng codual0dg.dot -o codual0dg.png

```

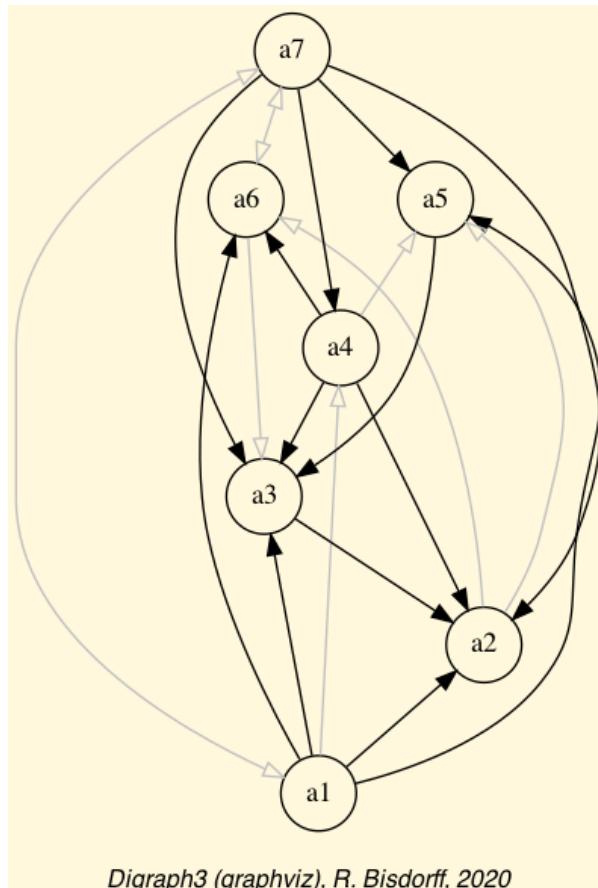


Fig. 1.10: The strict (codual) outranking digraph

It becomes readily clear now from the picture above that both alternatives *a1* and *a7* are *not outranked* by any other alternatives. Hence, *a1* and *a7* appear as *weak Condorcet*

winners (page 129) and may be recommended as potential *best decision actions* in a selection decision problem.

Many more tools for exploiting bipolar-valued outranking digraphs are available in the *Digraph3* resources (see the technical documentation of the outrankingDigraphs module and the perfTabs module).

Historical Notes

The seminal work on outranking digraphs goes back to the seventies and eighties when *Bernard Roy* joined the just starting *University Paris-Dauphine* and founded there the *Laboratoire d'Analyse et de Modélisation de Systèmes pour l'Aide à la Décision* (LAMSADE). The LAMSADE became the major site in the development of the outranking approach to multiple-criteria decision aiding ([ROY-1991]).

The ongoing success of the original *outranking* concept stems indeed from the fact that it is rooted in a sound pragmatism. The multiple-criteria performance tableau object, necessarily associated with a given outranking digraph, is indeed convincingly objective and meaningful ([ROY-1993]). And, ideas from social choice theory gave initially the insight that a pairwise voting mechanism à la *Condorcet* could provide an order-statistical tool for aggregating a set of preference points of view into what *Marc Barbut* called the *central Condorcet* point of view ([CON-1785] and [BAR-1980]); in fact the median of the multiple preference points of view, at minimal absolute *Kendall's* ordinal correlation distance from all individual points of view (see Ordinal correlation equals bipolar-valued relational equivalence).

Considering thus each performance criterion as a subset of unanimous voters and balancing the votes in favour against considerable counter-performances in disfavour gave eventually rise to the concept of *outranking situation*, a distinctive feature of the Multiple-Criteria Decision Aiding approach ([ROY-1991]). A modern definition would be: an alternative x is said to *outrank* alternative y when – a *significant majority* of criteria confirm that alternative x has to be considered as *at least as well evaluated as* an alternative y (the *concordance* argument); and – no discordant criterion opens to significant doubt the validity of the previous confirmation by revealing a considerable counter-performance of alternative x compared to y (the *discordance* argument).

If the concordance argument was always well received, the discordance argument however, very confused in the beginning ([ROY-1966], [BIS-2009]), could only be handled in an epistemically correct and logically sound way by using a bipolar-valued epistemic logic ([BIS-2013]). The outranking situation had consequently to receive an explicit *negative* definition: An alternative x is said to *do not outrank* an alternative y when – a *significant majority* of criteria confirm that alternative x has to be considered as *not at least as well evaluated as* alternative y ; and – no discordant criterion opens to significant doubt the validity of the previous confirmation by revealing a considerable *better* performance of alternative x compared to y .

Furthermore, the initial conjunctive aggregation of the concordance and discordance arguments had to be replaced by a disjunctive epistemic fusion operation, polarising in a logically sound and epistemically correct way the concordance with the discordance argument. This way, bipolar-valued outranking digraphs gained two very useful properties from a measure theoretical perspective. They are *strongly complete*; incomparability sit-

uations are no longer attested by the absence of positive outranking relations, but instead by epistemic indeterminateness. And, they verify the *coduality principle*: the negation of the epistemic ‘*at least as well evaluated as*’ situation corresponds formally to the strict converse epistemic ‘*less well evaluated than*’ situation.

Back to [Content Table](#) (page 1)

2 Evaluation and decision methods and tools

This is the methodological part of the tutorials.

- [Computing a best choice recommendation](#) (page 33)
- [How to create a new performance tableau instance](#) (page 54)
- [Generating random performance tableaux with the `randPerfTabs` module](#) (page 66)
- [Linearly ranking with multiple incommensurable criteria](#) (page 82)
- [On partially ranking outranking digraphs](#) (page 102)
- [Rating into relative performance quantiles](#) (page 111)
- [Rating with learned performance quantile norms](#) (page 117)
- [Computing the winner of an election with the `votingProfiles` module](#) (page 129)
- [On computing fair intergroup pairings](#) (page 141)
- [On computing fair intragroup pairings](#) (page 171)

2.1 Computing a best choice recommendation

“... *L'objectif des recherches était de mettre au point une méthode de résolution ... qui soit facile à utiliser, qui nécessite des hypothèses simples, aussi peu nombreuses et peu contestables que possible et qui puisse répondre aux besoins...*”⁶³ – B. Roy et al. (1966)

This tutorial presents the *RUBIS* best choice recommender system [BIS-2008]. Our approach is illustrated with a best office location selection problem. We show how to explore the given performance tableau and compute the corresponding bipolar-valued outranking digraph. After introducing the pragmatic principles that govern the *RUBIS* recommender algorithm, we present some tools for computing a first choice recommendation.

⁶³ “*The goal of our research was to design a resolution method ... that is easy to put into practice, that requires as few and reliable hypotheses as possible, and that meets the needs [of the decision maker] ...*” [ROY-1966]

- *What office location to choose ?* (page 34)
- *The performance tableau* (page 36)
- *The outranking digraph* (page 38)
- *Designing a best choice recommender system* (page 40)
- *Computing the first choice recommendation* (page 41)
- *Partially ranking the outranking digraph* (page 46)
- *Historical Notes* (page 50)

See also

Lecture 7 notes from the MICS Algorithmic Decision Theory course: [[ADT-L7](#)].

What office location to choose ?

A SME, specialized in printing and copy services, has to move into new offices, and its CEO has gathered seven **potential office locations** (see Table 2.1).

Table 2.1: The potential new office locations

ID	Name	Address	Comment
A	Ave	Avenue de la liberté	High standing city center
B	Bon	Bonnevoie	Industrial environment
C	Ces	Cessange	Residential suburb location
D	Dom	Dommeldange	Industrial suburb environment
E	Bel	Esch-Belval	New and ambitious urbanization far from the city
F	Fen	Fentange	Out in the countryside
G	Gar	Avenue de la Gare	Main city shopping street

Three **decision objectives** are guiding the CEO's choice:

1. *minimize* the yearly costs induced by the moving,
2. *maximize* the future turnover of the SME,
3. *maximize* the new working conditions.

The decision consequences to take into account for evaluating the potential new office locations with respect to each of the three objectives are modelled by the following **coherent family of criteria**²⁶.

²⁶ A *coherent family* of performance criteria verifies: a) *Exhaustiveness*: No argument acceptable to all stakeholders can be put forward to justify a preference in favour of action x versus action y when x and y have the same performance level on each of the criteria of the family; b) *Cohesiveness*: Stakeholders unanimously recognize that action x must be preferred to action y whenever the performance level of

Table 2.2: The coherent family of performance criteria

Objective	ID	Name	Comment
Yearly costs	C	Costs	Annual rent, charges, and cleaning
Future turnover	St	Standing	Image and presentation
Future turnover	V	Visibility	Circulation of potential customers
Future turnover	Pr	Proximity	Distance from town center
Working conditions	W	Space	Working space
Working conditions	Cf	Comfort	Quality of office equipment
Working conditions	P	Parking	Available parking facilities

The evaluation of the seven potential locations on each criterion are gathered in the following **performance tableau**.

Table 2.3: Performance evaluations of the potential office locations

Criterion	weight	A	B	C	D	E	F	G
Costs	45.0	35.0K€	17.8K€	6.7K€	14.1K€	34.8K€	18.6K€	12.0K€
Proximity	32.0	100	20	80	70	40	0	60
Visibility	26.0	60	80	70	50	60	0	100
Standing	23.0	100	10	0	30	90	70	20
Work. space	10.0	75	30	0	55	100	0	50
Work. comf.	6.0	0	100	10	30	60	80	50
Parking	3.0	90	30	100	90	70	0	80

Except the *Costs* criterion, all other criteria admit for grading a qualitative satisfaction scale from 0% (worst) to 100% (best). We may thus notice in Table 2.3 that location *A* (*Ave*) is the most expensive, but also 100% satisfying the *Proximity* as well as the *Standing* criterion. Whereas the locations *C* (*Ces*) is the cheapest one; providing however no satisfaction at all on both the *Standing* and the *Working Space* criteria.

In Table 2.3 we may also see that the *Costs* criterion admits the highest significance

x is significantly better than that of y on one of the criteria of positive weight, performance levels of x and y being the same on each of the other criteria; c) *Nonredundancy*: One of the above requirements is violated if one of the criteria is left out from the family. Source: European Working Group “*Multicriteria Aid for Decisions*” Series 3, no1, Spring, 2000.

(45.0), followed by the *Future turnover* criteria ($32.0 + 26.0 + 23.0 = 81.0$), The *Working conditions* criteria are the less significant ($10.0 + 6.0, + 3.0 = 19.0$). It follows that the CEO considers *maximizing the future turnover* the most important objective (81.0), followed by the *minizing yearly Costs* objective (45.0), and less important, the *maximizing working conditions* objective (19.0).

Concerning yearly costs, we suppose that the CEO is indifferent up to a performance difference of 1000€, and he actually prefers a location if there is at least a positive difference of 2500€. The grades observed on the six qualitative criteria (measured in percentages of satisfaction) are very subjective and rather imprecise. The CEO is hence indifferent up to a satisfaction difference of 10%, and he claims a significant preference when the satisfaction difference is at least of 20%. Furthermore, a satisfaction difference of 80% represents for him a *considerably large* performance difference, triggering an outranking *polarisation* the case given (see [BIS-2013]).

The performance tableau

A Python encoded performance tableau is available for downloading here [officeChoice.py](#).

We may inspect the performance tableau data with the computing resources provided by the perfTabs module.

```

1  >>> from perfTabs import PerformanceTableau
2  >>> t = PerformanceTableau('officeChoice')
3  >>> t
4  *----- PerformanceTableau instance description -----*
5  Instance class      : PerformanceTableau
6  Instance name       : officeChoice
7  Actions             : 7
8  Objectives          : 3
9  Criteria            : 7
10 NaN proportion (%) : 0.0
11 Attributes          : ['name', 'actions', 'objectives',
12                           'criteria', 'weightPreorder',
13                           'NA', 'evaluation']
14 >>> t.showPerformanceTableau()
15 *----- performance tableau -----*
16   Criteria | 'C'        'Cf'       'P'        'Pr'       'St'       'V'        'W'
17   Weights  | 45.00     6.00      3.00      32.00     23.00     26.00     10.00
18   -----|-----
19   'Ave'    | -35000.00  0.00     90.00     100.00    100.00    60.00     75.00
20   'Bon'    | -17800.00  100.00   30.00     20.00     10.00     80.00     30.00
21   'Ces'    | -6700.00   10.00    100.00    80.00      0.00     70.00     0.00
22   'Dom'    | -14100.00  30.00    90.00     70.00     30.00     50.00     55.00
23   'Bel'    | -34800.00  60.00    70.00     40.00     90.00     60.00    100.00
24   'Fen'    | -18600.00  80.00     0.00      0.00     70.00      0.00     0.00
25   'Gar'    | -12000.00  50.00    80.00     60.00     20.00    100.00     50.00

```

We thus recover all the input data. To measure the actual preference discrimination we observe on each criterion, we may use the `showCriteria()` method.

```

1 >>> t.showCriteria(IntegerWeights=True)
2 ----- criteria -----
3 C 'Costs'
4 Scale = (Decimal('0.00'), Decimal('50000.00'))
5 Weight = 45
6 Threshold ind : 1000.00 + 0.00x ; percentile: 9.5
7 Threshold pref : 2500.00 + 0.00x ; percentile: 14.3
8 Cf 'Comfort'
9 Scale = (Decimal('0.00'), Decimal('100.00'))
10 Weight = 6
11 Threshold ind : 10.00 + 0.00x ; percentile: 9.5
12 Threshold pref : 20.00 + 0.00x ; percentile: 28.6
13 Threshold veto : 80.00 + 0.00x ; percentile: 90.5
14 ...

```

On the *Costs* criterion, 9.5% of the performance differences are considered insignificant and 14.3% below the preference discrimination threshold (lines 6-7). On the qualitative *Working Comfort* criterion, we observe again 9.5% of insignificant performance differences (line 11). Due to the imprecision in the subjective grading, we notice here 28.6% of performance differences below the preference discrimination threshold (Line 12). Furthermore, $100.0 - 90.5 = 9.5\%$ of the performance differences are judged *considerably large* (Line 13); 80% and more of satisfaction differences triggering in fact an outranking polarisation. Same information is available for all the other criteria.

A colorful comparison of all the performances is shown on Fig. 2.1 by the `heatmap` statistics, illustrating the respective quantile class of each performance. As the set of potential alternatives is tiny, we choose here a classification into performance quintiles.

```

>>> t.showHTMLPerformanceHeatmap(colorLevels=5,
...                                 rankingRule=None)

```

Heatmap of Performance Tableau 'officeChoice'

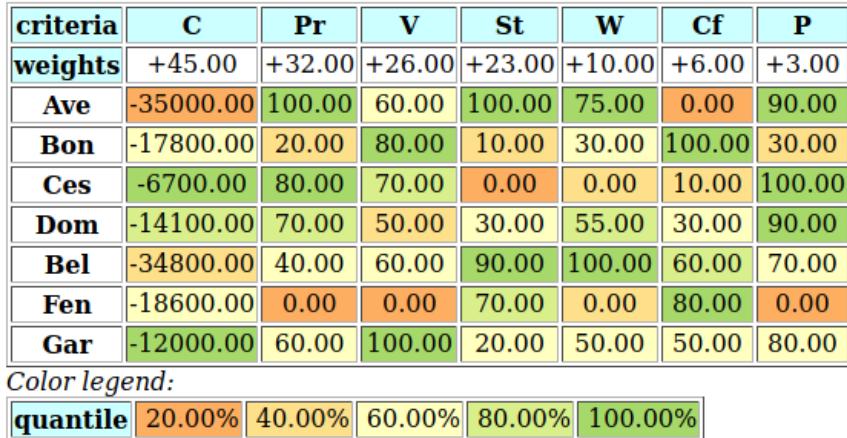


Fig. 2.1: Unranked heatmap of the location choice performance tableau

Location *A* (*Ave*) shows extreme and contradictory performances: highest *Costs* and no *Working Comfort* on one hand, and total satisfaction with respect to *Standing*, *Proximity* and *Parking facilities* on the other hand. Similar, but opposite, situation is given for location *C* (*Ces*): unsatisfactory *Working Space*, no *Standing* and no *Working Comfort* on the one hand, and lowest *Costs*, best *Proximity* and *Parking facilities* on the other hand. Contrary to these contradictory alternatives, we observe two appealing compromise decision alternatives: locations *D* (*Dom*) and *G* (*Gar*). Finally, location *F* (*Fen*) is clearly the less satisfactory alternative of all.

In view of Fig. 2.1, what is now the office location we may recommend to the CEO as **best choice** ?

The outranking digraph

To help the CEO choosing the best office location, we are going to compute pairwise outrankings (see [BIS-2013]) on the set of potential locations. For two locations *x* and *y*, the situation “*x outranks y*”, denoted $(x \succsim y)$, is given when there is:

1. a **significant majority** of criteria concordantly supporting that location *x* is *at least as well evaluated as* location *y*, and
2. **no considerable** counter-performance observed on any discordant criterion.

The credibility of each pairwise outranking situation (see [BIS-2013]), denoted $r(x \succsim y)$, is by default measured in a bipolar significance valuation $[-1.00, 1.00]$, where **positive** terms $r(x \succsim y) > 0.0$ indicate a **validated**, and **negative** terms $r(x \succsim y) < 0.0$ indicate a **non-validated** outrankings; whereas the **median** value $r(x \succsim y) = 0.0$ represents an **indeterminate** situation (see [BIS-2004a]).

For computing such a bipolar-valued outranking digraph from the given performance tableau *t*, we use the `BipolarOutrankingDigraph` class constructor from the `outrankingDigraphs` module. The `showHTMLRelationTable` method shows below the resulting bipolar-valued adjacency matrix in a system browser window (see Fig. 2.2).

```

1 >>> from outrankingDigraphs import BipolarOutrankingDigraph
2 >>> g = BipolarOutrankingDigraph(t)
3 >>> g.showHTMLRelationTable()

```

Valued Adjacency Matrix

r(x S y)	A	B	C	D	E	F	G
A	-	0.00	1.00	0.30	0.78	0.00	0.00
B	0.00	-	0.00	-0.56	0.00	1.00	-0.60
C	0.00	0.00	-	0.46	0.00	1.00	0.10
D	0.10	0.56	0.02	-	0.46	1.00	0.25
E	0.52	0.00	0.00	-0.10	-	1.00	-0.42
F	0.00	-1.00	-1.00	-1.00	-1.00	-	-1.00
G	0.00	0.92	-0.10	1.00	0.54	1.00	-

Valuation domain: [-1.00; +1.00]

Fig. 2.2: The office choice outranking digraph

In Fig. 2.2 we may notice that Alternative D is **positively outranking** all other potential office locations. D is hence a *Condorcet winner*. Yet, alternatives A (the most expensive) and C (the cheapest) are *not* outranked by any other locations; they are in fact **weak Condorcet winners**.

```

1 >>> g.computeCondorcetWinners()
2      ['D']
3 >>> g.computeWeakCondorcetWinners()
4      ['A', 'C', 'D']

```

For two locations x and y , the situation “ x strictly outranks y ”, denoted $(x \succ y)$, is given when x outranks y and y does not outrank y . From theory, we know that outranking digraphs are *strongly complete*, i.e. for all x and y in X , $r(x \succ y) + r(y \succ x) \geq 0.0$. And they verify the *coduality principle*: $r(x \not\succ y) = r(y \not\succ x)$ (see On characterizing bipolar-valued outranking digraphs and [BIS-2013]).

We may hence compute a strict outranking digraph gcd with the *codual transform*, i.e. the *converse of the negation* (see Line 1 below) of digraph g (see tutorial on *Working with the outrankingDigraphs module* (page 25)).

```

1 >>> gcd = ~(-g) # codual transform
2 >>> gcd
3 *----- Object instance description -----*
4 Instance class      : BipolarOutrankingDigraph
5 Instance name       : converse-dual-rel_officeChoice
6 Actions             : 7

```

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```

7 Criteria : 7
8 Size : 10
9 Determinateness (%) : 71.43
10 Valuation domain : [-1.00;1.00]
11 Attributes : ['actions', 'ndigits', 'valuationdomain',
12           'objectives', 'criteria', 'evaluation',
13           'NA', 'order', 'gamma', 'notGamma',
14           'name', 'relation']

```

We observe in the resulting strict outranking digraph gcd 10 valid strict outranking situations (see Line 8) on which we are going to focus our search for a best choice recommendation.

Designing a best choice recommender system

Solving a best-choice problem consists traditionally in finding *the* unique best decision alternative. We adopt here instead a modern **recommender system** approach which shows a non empty subset of decision alternatives which contains by construction the potential best alternative(s).

The five *pragmatic principles* for computing such a *best choice recommendation* (BCR) are the following

- **P1:** *Elimination for well motivated reasons (external stability)*; each eliminated alternative has to be strictly outranked by at least one alternative in the BCR.
- **P2:** *Minimal size*; the BCR must be as limited in cardinality as possible.
- **P3:** *Efficient and informative (internal stability)*; The BCR must not contain a self-contained sub-recommendation.
- **P4:** *Effectively better*; the BCR must not be ambiguous in the sense that it may not be both a first choice as well as a last choice recommendation.
- **P5:** *Maximally determined*; the BCR is, of all potential best-choice recommendations, the most determined one in the sense of the epistemic characteristics of the bipolar-valued outranking relation.

Let X be the set of potential decision alternatives. Let Y be a non empty subset of X , called a *choice* in the strict outranking digraph $G(X, r(\succsim))$. We can now qualify a BCR Y in following terms:

- Y is called strictly *outranking* (resp. *outranked*) when for all not selected alternative x there exists an alternative y in X retained such that $r(y \succsim x) > 0.0$ (resp. $r(x \succsim y) > 0.0$). Such a choice verifies the external stability (principle **P1**).
- Y is called *weakly independent* when for all x not equal y in Y we observe $r(x \succsim y) \leq 0.0$. Such a choice verifies the internal stability (principle **P3**).
- Y is conjointly a strictly *outranking* (resp. *outranked*) **and** *weakly independent* choice. Such a choice is called an *initial* (resp. *terminal*) *prekernel* (see the tutorial

on computing digraph kernels). The initial prekernel now verifies principles **P1**, **P2**, **P3** and **P4**.

- To finally verify principle **P5**, we recommend among all potential initial prekernels, a *most determined* one, i.e. a strictly *outranking* and *weakly independent* choice supported by the highest criteria significance. And in this most determined initial prekernel we eventually retain the alternative(s) that are included with highest criteria significance (see the tutorial on Computing bipolar-valued kernel membership characteristic vectors).

Mind that a given strict outranking digraph may not always admit prekernels. This is the case when the digraph contains chordless circuits of odd length. Luckily, our strict outranking digraph *gcd* here does not show any chordless outranking circuits; a fact we can check with the `showChordlessCircuits()` method.

```
1 >>> gcd.showChordlessCircuits()
2 No circuits observed in this digraph.
```

When observing chordless odd outranking circuits, we need to break them open with the `digraphs.BrokenCocsDigraph` class at their weakest link, before enumerating the prekernels.

We are ready now for building a first choice recommendation.

Computing the first choice recommendation

Following the previously stated pragmatic principles, potential first choice recommendations are determined by the initial prekernels –*weakly independent* and *strictly outranking* choices– of the strict outranking digraph (see the tutorial on computing digraph kernels). Any detected chordless odd outranking circuits are by default broken up (see [BIS-2008]).

Listing 2.1: Computing the first choice recommendation

```
1 >>> g.showFirstChoiceRecommendation(ChoiceVector=True)
2 * --- First and last choice recommendation(s) ---
3 (in decreasing order of determinateness)
4 Credibility domain: [-1.00,1.00]
5 === >> potential first choice(s)
6 * choice : ['A', 'C', 'D']
7 independence : 0.00
8 dominance : 0.10
9 absorbency : 0.00
10 covering (%) : 41.67
11 determinateness (%) : 50.59
12 - characteristic vector = { 'D': 0.02, 'G': 0.00, 'C': 0.00,
13                               'A': 0.00, 'F': -0.02, 'E': -0.02,
14                               'B': -0.02, }
15 === >> potential last choice(s)
16 * choice : ['A', 'F']
17 independence : 0.00
```

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```

18 dominance : -0.52
19 absorbency : 1.00
20 covered (%) : 50.00
21 determinateness (%) : 50.00
22 - characteristic vector = { 'G': 0.00, 'F': 0.00, 'E': 0.00,
23                               'D': 0.00, 'C': 0.00, 'B': 0.00,
24                               'A': 0.00, }
```

It is interesting to notice in Listing 2.1 (Line 6) that the **first choice recommendation** consists actually in the set of weak Condorcet winners: ‘A’, ‘C’ and ‘D’. In the corresponding characteristic vector (see Lines 12-14), representing the bipolar credibility degree with which each alternative may indeed be considered a first choice candidate (see [BIS-2006a], [BIS-2006b]), we find confirmed that alternative *D* is the only positively validated one, whereas both extreme alternatives - *A* (the most expensive) and *C* (the cheapest) - stay in an *indeterminate* situation. They **may be or not be** potential first choice candidates besides *D*. Notice furthermore that location *G* is not included in the initial prekernel, yet, shows nevertheless an indeterminate situation with respect to *being or not being* a potential first choice candidate. Alternatives *B*, *E* and *F* are *negatively* included, i.e. *positively excluded* from this first choice recommendation. We may furthermore notice in Line 16 that both alternatives *A* and *F* are reported as potential *strict outranked* choices, hence as potential **last choice candidates**. The ambiguous first-ranked and last-ranked position of alternative *A* indicates its global incomparability status as shown in Fig. 2.3.

```

1 >>> gcd.exportGraphViz(fileName='bestChoiceChoice',
2                         firstChoice=['C','D'],
3                         lastChoice=['F'])
4 ----- exporting a dot file for GraphViz tools -----
5 Exporting to bestOfficeChoice.dot
6 dot -Grankdir=BT -Tpng bestOfficeChoice.dot -o bestOfficeChoice.png
```



Fig. 2.3: Best office choice recommendation from strict outranking digraph

To comprehend the indeterminate situation of location G , let us now compare the performances of alternatives D and G in a pairwise perspective (see below). With the given preference discrimination thresholds, we notice that alternative G is actually **certainly at least as good as** alternative D : $r(G \succsim D) = +145/145 = +1.0$ and alternative D is also positively, but less credibly, *at least as good as* alternative G : $r(D \succsim G) = +36/145 = +0.25$ (see Line 14 below).

1	>>> g.showPairwiseComparison('G','D')
2	*----- pairwise comparison -----*
3	Comparing actions : (G, D)
4	crit. wght. g(x) g(y) diff. ind pref (G,D)/(D,G) □
5	□
6	C 45.00 -12000.00 -14100.00 +2100.00 1000.00 2500.00 +45.00/+0.00 □
7	□
8	Cf 6.00 50.00 30.00 +20.00 10.00 20.00 +6.00/-6.00 □
9	□
10	P 3.00 80.00 90.00 -10.00 10.00 20.00 +3.00/+3.00 □
	□
	Pr 32.00 60.00 70.00 -10.00 10.00 20.00 +32.00/+32.00 □
	□
	St 23.00 20.00 30.00 -10.00 10.00 20.00 +23.00/+23.00 □

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11	↪	V	26.00	100.00	50.00	+50.00		10.00	20.00	+26.00/-26.00	◻
12	↪	W	10.00	50.00	55.00	-5.00		10.00	20.00	+10.00/+10.00	◻
13	↪										◻
=====											
14	↪	Valuation in range: [-145.00;+145.00]; global concordance: +145.00/+36.	00								

Yet, we must as well notice that the cheapest alternative C is in fact **strictly outranking** alternative G : $r(C \succsim G) = +15/145 > 0.0$, and $r(G \succsim C) = -15/145 < 0.0$ (see Line 14 below).

1	>>>	g.showPairwiseComparison('C','G')	*	----- pairwise comparison -----*							
2			Comparing actions : (C, G)/(G, C)								
3			crit. wght.	g(x)	g(y)	diff.		ind.	pref.	(C,G)/(G,C)	◻
4			↪								
5			◻								
=====											
6			C	45.00	-6700.00	-12000.00	+5300.00		1000.00	2500.00	+45.00/-45.
7			↪ 00								
8			Cf	6.00	10.00	50.00	-40.00		10.00	20.00	-6.00/+6.
9			↪ 00								
10			P	3.00	100.00	80.00	+20.00		10.00	20.00	+3.00/-3.
11			↪ 00								
12			Pr	32.00	80.00	60.00	+20.00		10.00	20.00	+32.00/-32.
13			↪ 00								
14			St	23.00	0.00	20.00	-20.00		10.00	20.00	-23.00/+23.
			↪ 00								
			V	26.00	70.00	100.00	-30.00		10.00	20.00	-26.00/+26.
			↪ 00								
			W	10.00	0.00	50.00	-50.00		10.00	20.00	-10.00/+10.
			↪ 00								
=====											
14			↪	Valuation in range: -145.00 to +145.00; global concordance: +15.00/-15.	00						

Following pragmatic principle **P3** –the required internal stability stating that a BCR should not contain a sub-recommendation– alternative G is hence dropped from our first-ranked list of alternatives. Yet, the credibility level of this outranking situation is not very high: $15/145 = 0.104$ (55.2% significance majority). Considering a potential imprecise knowledge of the different criteria significance weights, it appears opportune to compute in Listing 2.2 below a 90% confident outranking digraph (see the advanced topic on computing confident outrankings with uncertain criteria significance weights).

Listing 2.2: Computing a 90% confident first choice recommendation

```

1  >>> cg = ConfidentBipolarOutrankingDigraph(t,confidence=90.0)
2  >>> cg
3  *----- Object instance description -----*
4  Instance class      : ConfidentBipolarOutrankingDigraph
5  Instance name       : rel_officeChoice_CLT
6  Actions             : 7
7  Criteria            : 7
8  Size                : 16
9  Uncertainty model   : triangular(a=0,b=2w)
10 Likelihood domain    : [-1.0;+1.0]
11 Confidence level     : 0.80 (90.0%)
12 Confident credibility: > abs(0.104) (55.2%)
13 Determinateness (%)  : 70.67
14 Valuation domain     : [-1.00;1.00]
15 >>> cg.showFirstChoiceRecommendation()
16 ****
17 First choice recommendation(s) (BCR)
18 (in decreasing order of determinateness)
19 Credibility domain: [-1.00,1.00]
20 === >> potential first choice(s)
21 * choice           : ['A', 'C', 'D', 'G']
22   independence      : 0.00
23   dominance         : 0.42
24   absorbency        : 0.00
25   covering (%)      : 50.00
26   determinateness (%) : 50.00
27 - most credible action(s) = { }
28 === >> potential last choice(s)
29 * choice           : ['A', 'B', 'F']
30   independence      : 0.00
31   dominance         : 0.00
32   absorbency        : 1.00
33   covered (%)       : 50.00
34   determinateness (%) : 50.00
35 - most credible action(s) = { }

```

The `ConfidentBipolarOutrankingDigraph` class constructor assumes here that the criteria significance weights are in fact *triangular random variates* in the range 0 to 2 times the given significance weights (Line 9). With this working hypothesis, we obtain a 90% confident outranking digraph `cg` where three outranking situations with a credibility in the range $[-15/145; +15/145]$ are put to *indeterminate* (Line 8). The pairwise outranking situations between location *C* and location *G* are for instance not 90% confident and the first choice recommendation now includes consequently this latter location as a further potential best choice candidate (Line 21). Notice by the way that location ‘*D*’ is no more

a *Condorcet winner* as the alternative is not 90% confidently outranking location *C* (Line 27).

To get a further interesting insight in the overall outranking situation, we finally make usage of the new `PartialBachetRanking` class imported from the `transitiveDigraphs` module, for computing a **partial ranking** of all the potential office locations (see the advanced topic on *partially ranking strategies* (page 102)).

Partially ranking the outranking digraph

In Listing 2.3 Line 2, we operate the *epistemic disjunctive fusion* (page 17) of the five best correlated linear rankings obtained from 200 random Bachet rankings (see Lines 4-8). In the resulting transitive partial outranking relation, alternatives *A*, *C*, *D* as well as *G* appear all ranked before *B* and *E*, whereas alternative *F* appears always last-ranked (see Lines 11 and 14).

Listing 2.3: Partially ranking the location alternatives

```

1  >>> from transitiveDigraphs import PartialBachetRanking
2  >>> pbr = PartialBachetRanking(g,randomized=200,maxNbrOfRankings=5,
3  <--seed=4)
4  >>> pbr.bachetRankings
5  [(0.816, ['G', 'D', 'A', 'C', 'B', 'E', 'F']),
6  (0.788, ['G', 'D', 'E', 'B', 'A', 'C', 'F']),
7  (0.778, ['A', 'D', 'C', 'G', 'E', 'B', 'F']),
8  (0.758, ['D', 'A', 'C', 'G', 'E', 'B', 'F']),
9  (0.756, ['G', 'C', 'D', 'A', 'E', 'B', 'F])]
10 >>> pbr.showTransitiveDigraph()
11 Ranking by Choosing and Rejecting
12 1st ranked ['A', 'C', 'D', 'G']
13 2nd ranked ['B', 'E']
14 2nd last ranked ['B', 'E']
15 1st last ranked ['F']
16 >>> pbr.exportGraphViz('officeChoiceRanking',ArrowHeads=True)
17 *----- exporting a dot file for GraphViz tools -----*
18 Exporting to officeChoiceRanking.dot
dot -Grankdir=TB -Tpng officeChoiceRanking.dot -o officeChoiceRanking.
<--png

```

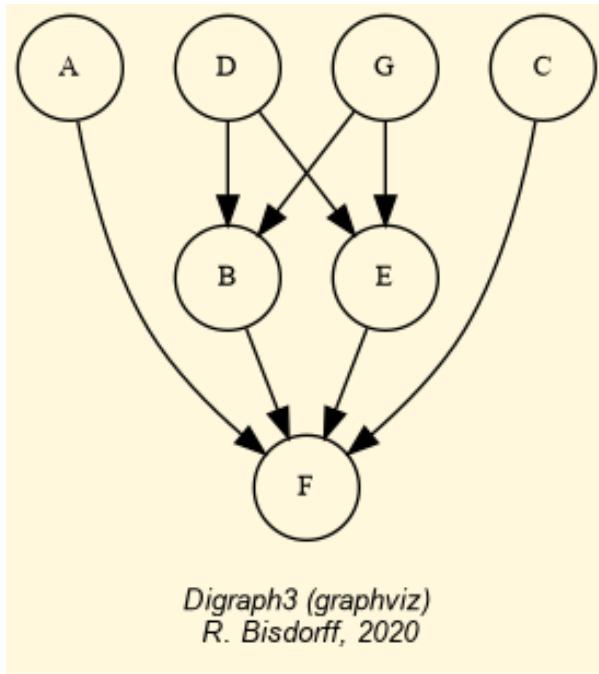


Fig. 2.4: Partially ranking the outranking digraph

Fig. 2.4 makes hence again clearly apparent the important fact that the most expensive location A and the cheapest location C , both, appear incomparable with all the other alternatives except the last-ranked location F . With the `computePartialOutrankingConsensusQuality()` method, we may check in Listing 2.4 the consensus quality of this partial ranking with respect to the marginal criterion rankings.

Listing 2.4: Consensus quality of the partial Bachtet ranking

```

1 >>> pbr.computePartialOutrankingConsensusQuality(Comments=True)
2 Consensus quality of partial ranking:
3 Criterion (weight)      : ordinal correlation
4 -----
5 Proximity (0.221)       : +1.000
6 Parking (0.021)         : +0.900
7 Visibility (0.179)       : +0.700
8 Costs (0.310)           : +0.500
9 Working Space (0.069)   : +0.500
10 Standing (0.159)        : -0.300
11 Comfort (0.041)         : -0.700
12 Summary:
13 Weighted mean marginal correlation (a) : +0.478
14 Standard deviation (b)                 : +0.476
15 Partial ranking fairness (a)-(b)       : +0.002

```

The partial *Bachtet* ranking is a 100% consistent with the *Proximity* criterion, 85% consistent with *Visibility* and 75% consistent with the *Costs* criterion. These three criteria

are the most significant ones (see Lines 5 and 7). The least considered criteria are the *Standing* and even more the *Comfort* criterion. The partial *Bachet* ranking is indeed only 35% consistent with the *Standing* and only 15% consistent with the latter one (see Lines 10-11). The mean weighted marginal ordinal correlation index (+0.478, Line 13) over all the criteria shows eventually a partial ranking consensus supported by a nearly 75% significance majority.

We may finally use the best, with the outranking digraph g correlated (+0.816), *Bachet* ranking [*G*, *D*, *A*, *C*, *B*, *E*, *F*] for showing in Fig. 2.5 a from best to worst ranked performance heatmap of all the potential office locations.

```
>>> t.showHTMLPerformanceHeatmap(actionsList=pbr.bachetRankings[0][1],
...                                Correlations=True)
```

Heatmap of Performance Tableau 'officeChoice'

criteria	P	Pr	V	Ct	W	St	Cf
weights	+3.00	+32.00	+26.00	+45.00	+10.00	+23.00	+6.00
tau(*)	+0.52	+0.52	+0.43	+0.31	+0.14	-0.14	-0.24
Gar	80.00	60.00	100.00	-12000.00	50.00	20.00	50.00
Dom	90.00	70.00	50.00	-14100.00	55.00	30.00	30.00
Ave	90.00	100.00	60.00	-35000.00	75.00	100.00	0.00
Ces	100.00	80.00	70.00	-6700.00	0.00	0.00	10.00
Bon	30.00	20.00	80.00	-17800.00	30.00	10.00	100.00
Bel	70.00	40.00	60.00	-34800.00	100.00	90.00	60.00
Fen	0.00	0.00	0.00	-18600.00	0.00	70.00	80.00

Color legend:

quantile	14.29%	28.57%	42.86%	57.14%	71.43%	85.71%	100.00%
-----------------	--------	--------	--------	--------	--------	--------	---------

(*) tau: *Ordinal (Kendall) correlation between marginal criterion and global ranking relation*

Outranking model: standard, Ranking rule: Bachet randomized

Ordinal (Kendall) correlation between

global ranking and global outranking relation: +0.816

Mean marginal correlation (a) : +0.277

Standard marginal correlation deviation (b) : +0.244

Ranking fairness (a) - (b) : +0.033

Fig. 2.5: The ranked performance heatmap of the potential office locations

In view of Fig. 2.5, office locations *G* or *D* make up convincing best choice recommendations with an apparent slight advantage for location *G*. Notice that both alternatives *A* and *C*, with their highly contrasted performance profiles, appear ranked in the midfield. Indeed, as they don't compare well, they may neither be first nor last ranked. This is why, when such largely incomparable or extreme alternatives are observed, linear rankings may fail to deliver adequate first-choice recommendations. Notice finally in the *tau* row above similar marginal ordinal correlation indexes as observed before in Listing 2.4 Lines 5-11.

The `digraphs.Digraph` class now readily provides the `showBachetChoiceRecommendation()` method for directly showing the first and

last choices obtained from the previous partial *Bachet* ranking result accessible in the *g.pbr* attribute (see Listing 2.5 Line 1).

Listing 2.5: Bachet choice recommendation

```

1  >>> g.showBachetChoiceRecommendation(randomized=200,seed=4)
2  ----- Bachet Choice Recommendations -----
3  Ranking by recursively first and last choosing
4  1st ranked ['A', 'C', 'D', 'G']
5  2nd ranked ['B', 'E']
6  2nd last ranked ['B', 'E']
7  1st last ranked ['F']
8  Quality of partial Bachet ranking
9  Crisp ordinal correlation : +1.000
10 Epistemic determination   : +0.337
11 Bipolar-valued equivalence : +0.337
12 Execution time: 0.207 seconds
13 >>> g.pbr
14 ----- Digraph instance description -----
15 Instance class      : PartialBachetRanking
16 Instance name       : converse-dual-rel_officeChoice_wk
17 Digraph Order       : 7
18 Digraph Size        : 10
19 Valuation domain    : [-1.00;1.00]
20 Determinateness (%) : 73.81
21 Attributes          : ['actions', 'ndigits', 'valuationdomain',
22                           'objectives', 'criteria', 'evaluation', 'NA',
23                           'order', 'runTimes', 'nbrThreads', 'startMethod
24   ↵',
25                           'gamma', 'notGamma', 'name', 'relation',
26                           'rankings', 'bachetRankings', 'randomized',
27                           'seed', 'maxNbrOfRankings', 'Polarised',
                           'partialBachetCorrelation', 'rankingByChoosing']
```

Due to the **Condorcet consistency** of the polarised *Bachet* ranking rule, the partial ranking digraph *g.pbr* represents here faithfully an actual transitive and asymmetrical part of the given outranking digraph *g* (see Line 13 and Bachet-Tutorial-label).

Our first choice recommendations eventually appear essentially depending on the very importance the CEO is attaching to each one of his three decision objectives. In the setting here, where he considers that *maximizing the future turnover* is the most important objective ($81/145 = 0.56$) followed by *minimizing the Costs* ($45/145 = 0.31$) and, less important, *maximizing the working conditions* ($19/145 = 0.13$), compromise locations *G* as well as *D* become the potential first choices candidates. However, if minimizing the *Costs* does not play much a role, it would perhaps be better to recommend the most advantageous location *A*; or if, on the contrary, the *Costs* objective does matter a lot, recommending the cheapest alternative *C* could definitely become the more convincing first choice recommendation.

It might be worth, as an **exercise**, to modify the criteria significance weights in the

‘officeChoice.py’ data file⁶⁴ in such a way that

- all three decision objectives are considered *equally important*, and
- all criteria under an objective are considered *equi-significant*.

What will become the best choice recommendation under this working hypothesis?

The next tutorial shows how to create or edit a performance tableau.

Historical Notes

The seminal article by *Bernard Roy* et al. about the outranking based best choice selection procedure called *ELECTRE* dates from 1966 and was actively promoted thereafter by the LAMSADE⁶¹, *Roy*’s research laboratory at the newly founded University Paris 9 Dauphine ([ROY-1966]). Our critical perspective on this seminal text may be consulted in [BIS-2009]. Revolutionary for that time was the idea to solve this classical decision problem not by looking for the **best** decision alternative, but **recommending**, with the help of the **kernel** of the outranking digraph, a *subset* of potential best choice candidates.

The originally proposed meticulous illustrative performance tableau may be modelled at present by the following performance tableau data stored under the name *roy66.py* in the *examples* directory of the Digraph3 resources.

Criteria Ident.	Actions' weight	Actions' performance grades						Grading Scale	Veto Threshold
		a1	a2	a3	a4	a5	a6		
g1	3	2	0	0	4	4	4	0-4	2.5
g2	3	4	1	2	1	2	2	0-4	2.5
g3	3	1	1	0	2	3	4	0-4	2.5
g4	1	2	4	4	2	2	3	0-4	2.5
g5	1	4	2	1	2	3	3	0-4	2.5

Underlining the fact that the *ELECTRE* method takes into account solely ordinal performance grades, the originally proposed actions’ grades were of ordinal linguistic nature: *bad*, *weak*, *average*, *good* and *excellent*. They have here arbitrarily been recoded as 0, 1, 2, 3 and 4. To show the usefulness of taking conjointly into account *concordance and discordance* arguments, an effective **veto discrimination threshold** of 2.5 is proposed, implying the polarisation of the outranking statements when the difference between two grades on a performance criterion is greater than two linguistic levels.

In Listing 2.6 below we compute the corresponding outranking digraph *g* (Lines 2-3).

Listing 2.6: The original ELECTRE best choice problem

```

1 >>> from outrankingDigraphs import *
2 >>> pt = PerformanceTableau('roy66')
3 >>> g = BipolarOutrankingDigraph(pt)

```

(continues on next page)

⁶⁴ The *officeChoice.py* data file may be found in the *examples* directory of the Digraph3 resources.

⁶¹ Laboratoires d’Analyse et de Modélisation de Systèmes d’Aide à la Décision, Université Paris-Dauphine, UMR 7243 CNRS.

(continued from previous page)

```

4 >>> ranking = g.computeNetFlowsRanking()
5 >>> ranking
6 ['a6', 'a5', 'a1', 'a4', 'a2', 'a3']
7 >>> g.showHTMLRelationTable(actionsList=ranking)
8 >>> g.showHTMLPerformanceHeatmap(colorLevels=5,actionsList=ranking)

```

Using the *NetFlows* ranking: $a6 > a5 > a1 > a4 > a2 > a3$ (Lines 6 and 7) we show in Fig. 2.6 below the corresponding **valued adjacency matrix**. The bipolar-valued outranking relation makes apparent that only the pair $(a1, a4)$ shows in fact mutual **vetoed outrankings** statements. All other polarisations are certainly confirming either a *valid* (+1.0) or an invalid (-1.0) pairwise outranking situation. One may furthermore notice that alternatives $a5$ and $a6$ are indifferent *Condorcet* winners, i.e. they outrank both all other alternatives. And, alternatives $a2$ and $a3$ are indifferent *Condorcet* losers, i.e. they are outranked by all the other alternatives.

Using again the same *NetFlows* ranking: $a6 > a5 > a1 > a4 > a2 > a3$ (Line 9), we show in Fig. 2.6 below also the corresponding very convincing **performance heatmap**.

Valued Adjacency Matrix

r(x \$ y)	a6	a5	a1	a4	a2	a3
a6	-	1.00	1.00	1.00	1.00	1.00
a5	0.27	-	0.27	1.00	1.00	1.00
a1	-1.00	-0.09	-	0.00	1.00	1.00
a4	-0.45	-0.27	0.00	-	1.00	1.00
a2	-1.00	-1.00	-1.00	-1.00	-	0.45
a3	-1.00	-1.00	-1.00	-1.00	0.27	-

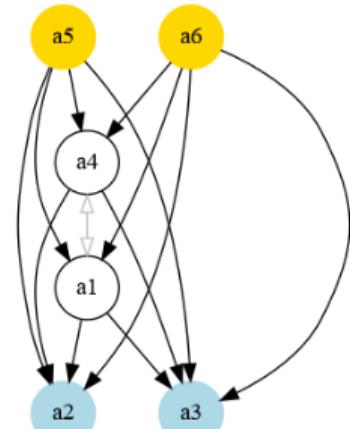
Valuation domain: [-1.00; +1.00]

Heatmap of Performance Tableau

criteria	g1	g2	g3	g4	g5
weights	+3.00	+3.00	+3.00	+1.00	+1.00
a6	20.00	10.00	20.00	13.00	13.00
a5	20.00	10.00	15.00	10.00	13.00
a1	10.00	20.00	5.00	10.00	16.00
a4	20.00	5.00	10.00	10.00	10.00
a2	0.00	5.00	5.00	16.00	10.00
a3	0.00	10.00	0.00	16.00	7.00

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------



Digraph3 (graphviz), R. Bisdorff, 2020

Fig. 2.6: Solving the seminal best choice recommendation problem

Finally, in Listing 2.7, our *Rubis* best choice recommendation confirms, with the help of the initial and terminal kernels of the corresponding strict outranking digraph (Lines

1,7 and 16), that alternatives a_6 and a_5 are potential first choice candidates and alternatives a_3 and a_2 are potential last choice candidates. The *graphviz* drawing of the strict outranking digraph, oriented by the initial and terminal kernels, shows its transitive structure (see Fig. 2.6).

Listing 2.7: The Rubis choice recommendation

```

1 >>> g.showRubisBestChoiceRecommendation(CoDual=True)
2 Rubis choice recommendation
3 ****
4 First choice recommendation(s) (BCR)
5 Credibility domain: [-1.00,1.00]
6 === >> potential first choice(s)
7 * choice : ['a5', 'a6']
8   independence : 0.27
9   dominance : 0.45
10  absorbency : -1.00
11  covering (%) : 100.00
12  determinateness (%) : 89.39
13  - first choice credibilities = { 'a6': 1.00, 'a5': 0.27,
14    'a4': -0.45, 'a3': -1.00, 'a2': -1.00, 'a1': -1.00, }
15 === >> potential last choice(s)
16 * choice : ['a2', 'a3']
17   independence : 0.27
18   dominance : -1.00
19   absorbency : 1.00
20   covered (%) : 100.00
21   determinateness (%) : 71.21
22   - last choice credibilities = { 'a3': 0.45, 'a2': 0.27,
23     'a6': -0.45, 'a5': -0.45, 'a4': -0.45, 'a1': -0.45, }
24 >>> (~(-g)).isTransitive()
25 True
26 >>> (~(-g)).exportGraphViz('roy66',firstChoice=['a6','a5'],
27 ...                               lastChoice=['a2','a3'])
28 ----- exporting a dot file for GraphViz tools -----
29 Exporting to roy66V1.dot
30 dot -Grankdir=BT -Tpng roy66.dot -o roy66.png

```

Following now a seminar presentation in 2005 at the LAMSADE, where the author promoted this usage of the strict outranking kernels as suitable candidates for delivering choice recommendations [BIS-2005], a critical discussion started about the methodological requirement for a convincing best choice recommendation to be *internally stable* (pragmatic principle **P3**). *Denis Bouyssou* illustrated his doubts with the potential outranking digraph shown in Fig. 2.7.

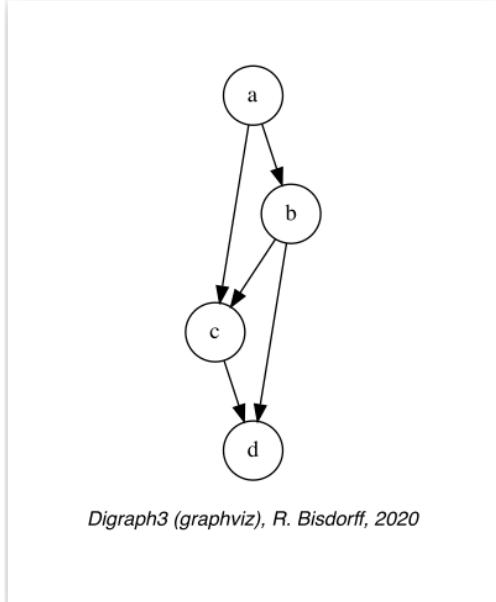


Fig. 2.7: The internal stability of a best choice recommendation in question

His commentary was the following: The only initial kernel of this digraph is the choice $\{a, d\}$. Yet, it is an ambiguous recommendation, as this choice is conjointly an *initial –outranking– and terminal –outranked– kernel*. If the instability of the best choice recommendation is, however, not considered a problem then the choice $\{a, b\}$ shows the most convincing strict outranking quality and could be recommended in priority as best choice candidates. Adding alternative d to the set of potential best choice candidates is not convincing as there exists in the given digraph the node b , which is better evaluated than d . The argument that the incomparability between a and d should favour d as potential best choice is interesting but another hypothesis could be that b perhaps outranks a . In this latter case, it seems clear that the actual best choice recommendation should be reduced to node b , unless one disposes of other information, like a performance tableau and/or the actual computation method of the outranking situations. In any case, one has to be very clear about the available information when judging a best choice procedure.

It became thereafter obvious for us all that both the lack of a specific performance tableau as well as the lack of a precisely defined algorithm for computing valid outranking situations do not allow to judge if a given digraph does indeed model a potential outranking relation. In our present bipolar-valued epistemic approach, a valid outranking digraph instance, following from a given performance tableau and the disjunctive epistemic fusion construction of the outranking relation, will necessarily verify the strong completeness condition and the coduality principle. As a consequence, incomparability situations are now modelled by *epistemic indeterminateness* and not by the actual absence of a reciprocal outranking relation.

The digraph put forward by *Bouyssou* in the October 2005 discussion is not strongly complete –node a is not outranking node d and vice versa– and does hence not represent, in our present sense, a valid outranking digraph instance. Yet, it may be a partial tournament and as such it could be a strict outranking digraph, i.e. the asymmetrical part –the codual– of a valid outranking digraph. In this case, nodes a and d –the kernel of the strict outranking digraph– would actually positively outrank each other

and, hence, represent both indifferently the natural best choice candidates. However, in this not strict outranking digraph, node a becomes also the unique *Condorcet* winner –positively outranking all other nodes– and gives hence the evident unique best choice recommendation.

Only after 2013, when the strong completeness and the coduality properties of the outranking digraph were discovered, became it obvious that the initial prekernels of the strict outranking digraph, coupled with the solution of the corresponding kernel equation system, could in fact deliver convincing best choice recommendations (see [BIS-2013]). Yet, *Bouyssou* and the critical audience of the 2005 seminar would be satisfied to see their doubts somehow confirmed by the solution of the office location choice problem shown previously. Indeed, the initial prekernel $\{A, C, D\}$ of the corresponding strict outranking digraph does not retain location G –as it is actually strictly outranked by location C – and proposes solely location D as credible best choice candidate. This latter location appears however certainly outranked by location G . Keeping location G in an indeterminate situation with being or not being a potential best choice candidate in the solution of the corresponding kernel equation system shows that the resulting bipolar-valued choice vector may be an essential complement of information. Showing solely an initial prekernel appears hence not necessarily sufficient for determining the actual best choice alternative(s). Similarly, questioning the confidence of outranking statements showing, the case given, weak positive credibilities, may result in a more convincing first-choice recommendation.

But it is the new *Bachet partial ranking rule* (page 102) that allows nowadays to compute a partial transitive tournament, very close in a bipolar-valued ordinal correlation sense to the actual transitive part of the given strict outranking digraph, that definitely supports our kernels based recommending approach. The unique initial and terminal kernels of such a transitive asymmetric digraph, easily found via a topological sort algorithm, may indeed deliver more effectively convincing first and/or last choice recommendations.

See also

- *Alice's best choice: A selection case study* (page 183)
- Lecture 7 notes from the MICS Algorithmic Decision Theory course: [ADT-L7].

Back to *Content Table* (page 1)

2.2 How to create a new performance tableau instance

- *Editing a template file* (page 55)
- *Editing the decision alternatives* (page 57)
- *Editing the decision objectives* (page 58)
- *Editing the family of performance criteria* (page 59)

- *Editing the performance table* (page 62)
- *Inspecting the template outranking relation* (page 63)
- *Ranking the template peformance tableau* (page 65)

In this tutorial we illustrate a way of creating a new `PerformanceTableau` instance by editing a template with 5 decision alternatives, 3 decision objectives and 6 performance criteria.

Editing a template file

For this purpose we provide the following `perfTab_Template.py` file in the `examples` directory of the **Digraph3** resources.

Listing 2.8: `PerformanceTableau` object template

```

1 ##########
2 # Digraph3 documentation
3 # Template for creating a new PerformanceTableau instance
4 # (C) R. Bisdorff Mar 2021
5 # Digraph3/examples/perfTab_Template.py
6 #####
7 from decimal import Decimal
8 from collections import OrderedDict
9 #####
10 # edit the decision actions
11 # avoid special characters, like '_', '/' or ':',
12 # in action identifiers and short names
13 actions = OrderedDict([
14     ('a1', {
15         'shortName': 'action1',
16         'name': 'decision alternative a1',
17         'comment': 'some specific features of this alternative',
18     }),
19     ...
20     ...
21 ])
22 #####
23 # edit the decision objectives
24 # adjust the list of performance criteria
25 # and the total weight (sum of the criteria weights)
26 # per objective
27 objectives = OrderedDict([
28     ('obj1', {
29         'name': 'decision objective obj1',
30         'comment': "some specific features of this objective",
31         'criteria': ['g1', 'g2'],

```

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```
32     'weight': Decimal('6'),
33 ),
34 ...
35 ...
36 ])
#####
37 # edit the performance criteria
38 # adjust the objective reference
39 # Left Decimal of a threshold = constant part and
40 # right Decimal = proportional part of the threshold
41
42 criteria = OrderedDict([
43     ('g1', {
44         'shortName': 'crit1',
45         'name': "performance criteria 1",
46         'objective': 'obj1',
47         'preferenceDirection': 'max',
48         'comment': 'measurement scale type and unit',
49         'scale': (Decimal('0.0'), Decimal('100.0')),
50         'thresholds': {'ind': (Decimal('2.50'), Decimal('0.0')),
51                         'pref': (Decimal('5.00'), Decimal('0.0')),
52                         'veto': (Decimal('60.00'), Decimal('0.0'))
53                     },
54         'weight': Decimal('3'),
55     }),
56 ...
57 ...
58 ])
#####
59 # default missing data symbol = -999
60 NA = Decimal('-999')
61 #####
62 # edit the performance evaluations
63 # criteria to be minimized take negative grades
64
65 evaluation = {
66     'g1': {
67         'a1': Decimal("41.0"),
68         'a2': Decimal("100.0"),
69         'a3': Decimal("63.0"),
70         'a4': Decimal('23.0'),
71         'a5': NA,
72     },
73     # g2 is of ordinal type and scale 0-10
74     'g2': {
75         'a1': Decimal("4"),
76         'a2': Decimal("10"),
77         'a3': Decimal("6"),
```

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```

78     'a4':Decimal('2'),
79     'a5':Decimal('9'),
80   },
81   # g3 has preferenceDirection = 'min'
82   'g3': {
83     'a1':Decimal("-52.2"),
84     'a2':NA,
85     'a3':Decimal("-47.3"),
86     'a4':Decimal('-35.7'),
87     'a5':Decimal('-68.00'),
88   },
89   ...
90   ...
91 }
92 #####

```

The template file, shown in Listing 2.8, contains first the instructions to import the required *Decimal* and *OrderedDict* classes (see Lines 7-8). Four main sections are following: the potential decision **actions**, the decision **objectives**, the performance **criteria**, and finally the performance **evaluation**.

Editing the decision alternatives

Decision alternatives are stored in attribute **actions** under the *OrderedDict* format (see the *OrderedDict* (<https://docs.python.org/3/library/collections.html>) description in the Python documentation).

Required attributes of each decision alternative, besides the object **identifier**, are: **shortName**, **name** and **comment** (see Lines 15-17). The *shortName* attribute is essentially used when showing the performance tableau or the performance heatmap in a browser view.

Note

Mind that graphviz drawings require digraph actions' (nodes) identifier strings without any special characters like `_` or `/`.

Decision actions descriptions are stored in the order of which they appear in the stored instance file. The *OrderedDict* object keeps this given order when iterating over the decision alternatives.

The random performance tableau models presented in the previous tutorial use the *actions* attribute for storing special features of the decision alternatives. The *Cost-Benefit* model, for instance, uses a **type** attribute for distinguishing between *advantageous*, *neutral* and *cheap* alternatives. The *3-Objectives* model keeps a detailed record of the performance profile per decision objective and the corresponding random generators per performance criteria (see Lines 7- below).

```

1  >>> t = Random3ObjectivesPerformanceTableau()
2  >>> t.actions
3  OrderedDict([
4      ('p01', {'shortName': 'p01',
5          'name': 'action p01 Eco~ Soc- Env+', 
6          'comment': 'random public policy',
7          'Eco': 'fair',
8          'Soc': 'weak',
9          'Env': 'good',
10         'profile': {'Eco': 'fair',
11             'Soc': 'weak',
12             'Env': 'good'}
13         'generators': {'ec01': ('triangular', 50.0, 0.5),
14                         'so02': ('triangular', 30.0, 0.5),
15                         'en03': ('triangular', 70.0, 0.5),
16                         ...
17                     },
18     },
19     ),
20     ...
21 ])

```

The second section of the template file concerns the decision *objectives*.

Editing the decision objectives

The minimal required attributes (see Listing 2.8 Lines 27-33) of the ordered decision **objectives** dictionary, besides the individual objective identifiers, are **name**, **comment**, **criteria** (the list of significant performance criteria) and **weight** (the importance of the decision objective). The latter attribute contains the sum of the *significance* weights of the objective's criteria list.

The **objectives** attribute is methodologically useful for specifying the performance criteria significance in building decision recommendations. Mostly, we assume indeed that decision objectives are all equally important and the performance criteria are equi-significant per objective. This is, for instance, the default setting in the random 3-*Objectives* performance tableau model.

Listing 2.9: Example of decision objectives' description

```

1  >>> t = Random3ObjectivesPerformanceTableau()
2  >>> t.objectives
3  OrderedDict([
4      ('Eco',
5          {'name': 'Economical aspect',
6          'comment': 'Random3ObjectivesPerformanceTableau generated',
7          'criteria': ['ec01', 'ec06', 'ec09'],
8          'weight': Decimal('48')}),

```

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```
9 ('Soc',
10   {'name': 'Societal aspect',
11    'comment': 'Random3ObjectivesPerformanceTableau generated',
12    'criteria': ['so02', 'so12'],
13    'weight': Decimal('48')}),
14 ('Env',
15   {'name': 'Environmental aspect',
16    'comment': 'Random3ObjectivesPerformanceTableau generated',
17    'criteria': ['en03', 'en04', 'en05', 'en07',
18                 'en08', 'en10', 'en11', 'en13'],
19    'weight': Decimal('48')})
20 ])
```

The importance weight sums up to 48 for each one of the three example decision objectives shown in Listing 2.9 (Lines 8,13 and 19), so that the significance of each one of the 3 economic criteria is set to 16, of both societal criteria is set to 24, and of each one of the 8 environmental criteria is set to 8.

Note

Mind that the **objectives** attribute is always present in a *PerformanceTableau* object instance, even when empty. In this case, we consider that each performance criterion canonically represents in fact its own decision objective. The criterion significance equals in this case the corresponding decision objective's importance weight.

The third section of the template file concerns now the *performance criteria*.

Editing the family of performance criteria

In order to assess how well each potential decision alternative is satisfying a given decision objective, we need *performance criteria*, i.e. decimal-valued grading functions gathered in an ordered **criteria** dictionary. The required attributes (see Listing 2.10), besides the criteria identifiers, are the usual **shortName**, **name** and **comment**. Specific for a criterion are furthermore the **objective** reference, the significance **weight**, the grading **scale** (minimum and maximum performance values), the **preferenceDirection** ('max' or 'min') and the performance discrimination **thresholds**.

Listing 2.10: Example of performance criteria description

```
1 criteria = OrderedDict([
2   ('g1', {
3     'shortName': 'crit1',
4     'name': "performance criteria 1",
5     'comment': 'measurement scale type and unit',
6     'objective': 'obj1',
7     'weight': Decimal('3'),
```

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```
8   'scale': (Decimal('0.0'), Decimal('100.0')),
9   'preferenceDirection': 'max',
10  'thresholds': {'ind': (Decimal('2.50'), Decimal('0.0')),
11      'pref': (Decimal('5.00'), Decimal('0.0')),
12      'veto': (Decimal('60.00'), Decimal('0.0'))
13    },
14  },
15  ...
16  ...])
```

In our bipolar-valued outranking approach, all performance criteria implement *decimal-valued* grading functions, where preferences are either *increasing* or *decreasing* with measured performances.

Note

In order to model a **coherent** performance tableau, the decision criteria must satisfy two methodological requirements:

1. **Independance**: Each decision criterion implements a grading that is *functionally independent* of the grading of the other decision criteria, i.e. the performance measured on one of the criteria does not *constrain* the performance measured on any other criterion.
2. **Non redundancy**: Each performance criterion is only *significant* for a *single* decision objective.

In order to take into account any, usually *unavoidable*, **imprecision** of the performance grading procedures, we may specify three performance **discrimination thresholds**: an **indifference** ('ind'), a **preference** ('pref') and a **considerable performance difference** ('veto') threshold (see Listing 2.10 Lines 10-12). The left decimal number of a threshold description tuple indicates a *constant part*, whereas the right decimal number indicates a proportional part.

On the template performance criterion *g1*, shown in Listing 2.10, we observe for instance a grading scale from 0.0 to 100.0 with a constant *indifference* threshold of 2.5, a constant *preference* threshold of 5.0, and a constant *considerable performance difference* threshold of 60.0. The latter threshold will trigger, the case given, a *polarisation* of the outranking statement [BIS-2013].

In a random *Cost-Benefit* performance tableau model we may obtain by default the following content.

Listing 2.11: Example of cardinal Costs criterion

```
1  >>> tcb = RandomCBPerformanceTableau()
2  >>> tcb.showObjectives()
3  *----- decision objectives -----"
```

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```

4   C: Costs
5     c1 random cardinal cost criterion 6
6     Total weight: 6.00 (1 criteria)
7
8     ...
9
10    >>> tcb.criteria
11    OrderedDict([
12      ('c1', {'preferenceDirection': 'min',
13              'scaleType': 'cardinal',
14              'objective': 'C',
15              'shortName': 'c1',
16              'name': 'random cardinal cost criterion',
17              'scale': (0.0, 100.0),
18              'weight': Decimal('6'),
19              'randomMode': ['triangular', 50.0, 0.5],
20              'comment': 'Evaluation generator: triangular law ...',
21              'thresholds':
22                OrderedDict([
23                  ('ind', (Decimal('1.49'), Decimal('0'))),
24                  ('pref', (Decimal('3.7'), Decimal('0'))),
25                  ('veto', (Decimal('67.71'), Decimal('0'))))
26                ]))
27
28    ...
29  ])

```

Criterion *c1* appears here (see Listing 2.11) to be a cardinal criterion to be minimized and significant for the *Costs* (*C*) decision objective. We may use the `showCriteria()` method for printing the corresponding performance discrimination thresholds.

```

1  >>> tcb.showCriteria(IntegerWeights=True)
2  ----- criteria -----
3  c1 'Costs/random cardinal cost criterion'
4  Scale = (0.0, 100.0)
5  Weight = 6
6  Threshold ind : 1.49 + 0.00x ; percentile: 5.13
7  Threshold pref : 3.70 + 0.00x ; percentile: 10.26
8  Threshold veto : 67.71 + 0.00x ; percentile: 96.15

```

The *indifference* threshold on this criterion amounts to a constant value of 1.49 (Line 6 above). More or less 5% of the observed performance differences on this criterion appear hence to be **insignificant**. Similarly, with a preference threshold of 3.70, about 90% of the observed performance differences are preferentially **significant** (Line 7). Furthermore, $100.0 - 96.15 = 3.85\%$ of the observed performance differences appear to be **considerable** (Line 8) and will trigger a *polarisation* of the corresponding outranking statements.

After the performance criteria description, we are ready for recording the actual *perf-*

mance table.

Editing the performance table

The individual grades of each decision alternative on each decision criterion are recorded in a double *criterion x action* dictionary called **evaluation** (see Listing 2.12). As we may encounter missing data cases, we previously define a *missing data* symbol **NA** which is set here to a value disjoint from all the measurement scales, by default *Decimal('999')* (Line 2).

Listing 2.12: Editing performance grades

```
1 #-----
2 NA = Decimal('999')
3 #-----
4 evaluation = {
5     'g1': {
6         'a1': Decimal("41.0"),
7         'a2': Decimal("100.0"),
8         'a3': Decimal("63.0"),
9         'a4': Decimal('23.0'),
10        'a5': NA,  # missing data
11    },
12    ...
13    ...
14    # g3 has preferenceDirection = 'min'
15    'g3': {
16        'a1': Decimal("-52.2"), # negative grades
17        'a2': NA,
18        'a3': Decimal("-47.3"),
19        'a4': Decimal('-35.7'),
20        'a5': Decimal(' -68.00'),
21    },
22    ...
23    ...
24 }
```

Notice in Listing 2.12 (Lines 16-) that on a criterion with *preferenceDirection = 'min'* all performance grades are recorded as **negative** values.

We may now inspect the eventually recorded complete template performance table.

```
1 >>> from perfTabs import PerformanceTableau
2 >>> t = PerformanceTableau('perfTab_Template')
3 >>> t.showPerformanceTableau(ndigits=1)
4 *---- performance tableau ----*
5 Criteria | 'g1'   'g2'   'g3'   'g4'   'g5'   'g6'
6 Actions  |   3     3     6     2     2     2
7 -----|-----
```

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8	'action1'		41.0	4.0	-52.2	71.0	63.0	22.5
9	'action2'		100.0	10.0	NA	89.0	30.7	75.0
10	'action3'		63.0	6.0	-47.3	55.4	63.5	NA
11	'action4'		23.0	2.0	-35.7	83.5	37.5	54.9
12	'action5'		NA	9.0	-68.0	10.0	88.0	75.0

We may furthermore compute the associated outranking digraph and check if we observe any polarised outranking situations.

```

1 >>> from outrankingDigraphs import BipolarOutrankingDigraph
2 >>> g = BipolarOutrankingDigraph(t)
3 >>> g.showPolarisations()
4 ----- Negative polarisations -----
5 number of negative polarisations : 1
6 1: r(a4 >= a2) = -0.44
7 criterion: g1
8 Considerable performance difference : -77.00
9 Veto discrimination threshold      : -60.00
10 Polarisation: r(a4 >= a2) = -0.44 ==> -1.00
11 ----- Positive polarisations -----
12 number of positive polarisations: 1
13 1: r(a2 >= a4) = 0.56
14 criterion: g1
15 Considerable performance difference : 77.00
16 Counter-veto threshold          : 60.00
17 Polarisation: r(a2 >= a4) = 0.56 ==> +1.00

```

Indeed, due to the considerable performance difference (77.00) observed on performance criterion g_1 , alternative a_2 **for sure** outranks alternative a_4 , respectively a_4 **for sure** does not outrank a_2 .

Inspecting the template outranking relation

Let us have a look at the outranking relation table.

Listing 2.13: The template outranking relation

1	>>>	g.showRelationTable()
* ----- Relation Table -----		
3	r	'a1' 'a2' 'a3' 'a4' 'a5'
4	----- -----	
5	'a1'	+1.00 -0.44 -0.22 -0.11 +0.06
6	'a2'	+0.44 +1.00 +0.33 +1.00 +0.28
7	'a3'	+0.67 -0.33 +1.00 +0.00 +0.17
8	'a4'	+0.11 -1.00 +0.00 +1.00 +0.06
9	'a5'	-0.06 -0.06 -0.17 -0.06 +1.00

We may notice in the outranking relation table above (see Listing 2.13) that decision

alternative a_2 positively **outranks** all the other four alternatives (Line 6). Similarly, alternative a_5 is positively **outranked** by all the other alternatives (see Line 9). We may orient this way the *graphviz* drawing of the template outranking digraph.

```
>>> g.exportGraphViz(fileName= 'template',
...                     firstChoice =['a2'],
...                     lastChoice=['a5'])
*----- exporting a dot file for GraphViz tools -----*
Exporting to template.dot
dot -Grankdir=BT -Tpng template.dot -o template.png
```

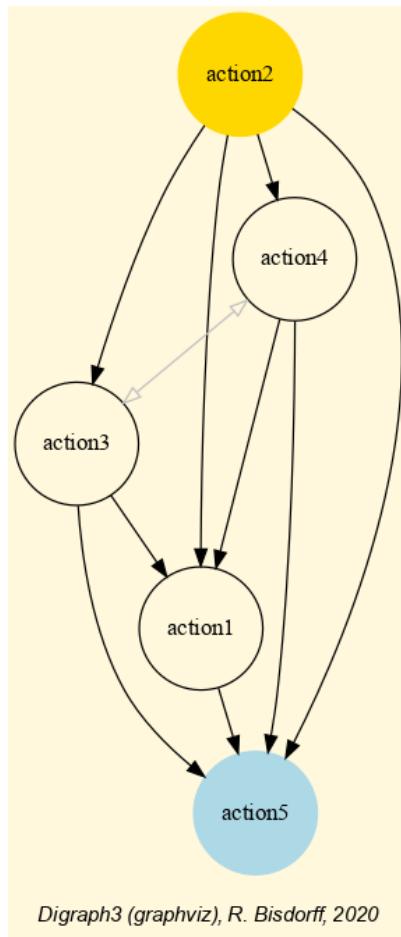


Fig. 2.8: The template outranking digraph

In Fig. 2.8 we may notice that the template outranking digraph models in fact a **partial order** on the five potential decision alternatives. Alternatives $action_3$ (' a_3 ') and $action_4$ (' a_4 ') appear actually **incomparable**. In Listing 2.13 their pairwise outranking characteristics show indeed the **indeterminate** value 0.00 (Lines 7-8). We may check their pairwise comparison as follows.

```
1 >>> g.showPairwiseComparison('a3','a4')
2 *----- pairwise comparison -----*
3 Comparing actions : (a3, a4)
```

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(continued from previous page)

	crit.	wght.	g(x)	g(y)	diff		ind	pref	r()	
<hr/>										
6	g1	3.00	63.00	23.00	+40.00		2.50	5.00	+3.00	
7	g2	3.00	6.00	2.00	+4.00		0.00	1.00	+3.00	
8	g3	6.00	-47.30	-35.70	-11.60		0.00	10.00	-6.00	
9	g4	2.00	55.40	83.50	-28.10		2.09	4.18	-2.00	
10	g5	2.00	63.50	37.50	+26.00		0.00	10.00	+2.00	
11	g6	NA	54.90							
12	Outranking characteristic value: r(a3 >= a4) = +0.00									
13	Valuation in range: -18.00 to +18.00									

The incomparability situation between 'a3' and 'a4' results here from a perfect balancing of positive (+8) and negative (-8) criteria significance weights.

Ranking the template performance tableau

We may eventually rank the five decision alternatives with a heatmap browser view following the *Copeland* ranking rule which consistently reproduces the partial outranking order shown in Fig. 2.8.

```
>>> g.showHTMLPerformanceHeatmap(ndigits=1,colorLevels=5,
...     Correlations=True,rankingRule='Copeland',
...     pageTitle='Heatmap of the template performance tableau')
```

Heatmap of the template performance tableau

criteria	crit4	crit1	crit3	crit2	crit6	crit5
weights	+2.00	+3.00	+6.00	+3.00	+2.00	+2.00
tau(*)	+0.60	+0.40	+0.35	+0.20	+0.10	-0.60
action2	89.0	100.0	NA	10.0	75.0	30.7
action3	55.4	63.0	-47.3	6.0	NA	63.5
action4	83.5	23.0	-35.7	2.0	54.9	37.5
action1	71.0	41.0	-52.2	4.0	22.5	63.0
action5	10.0	NA	-68.0	9.0	75.0	88.0

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation
Outranking model: **standard**, Ranking rule: **Copeland**

Ordinal (Kendall) correlation between global ranking and global outranking relation: **+1.000**
Mean marginal correlation (a) : **+0.228**

Standard marginal correlation deviation (b) : **+0.322**

Ranking fairness (a) - (b) : **-0.094**

Due to a 11 against 7 **plurality tyranny** effect, the *Copeland* ranking rule, essentially based on crisp majority outranking counts, puts here alternative *action5* (*a5*) last, despite its excellent grades observed on criteria *g2*, *g5* and *g6*. A slightly **fairer** ranking result may be obtained with the *NetFlows* ranking rule.

```
>>> g.showHTMLPerformanceHeatmap(ndigits=1,colorLevels=5,
...     Correlations=True,rankingRule='NetFlows',
...     pageTitle='Heatmap of the template performance tableau')
```

Heatmap of the template performance tableau

criteria	crit2	crit6	crit1	crit4	crit3	crit5
weights	+3.00	+2.00	+3.00	+2.00	+6.00	+2.00
tau(*)	+0.60	+0.50	+0.40	+0.20	-0.05	-0.20
action2	10.0	75.0	100.0	89.0	NA	30.7
action3	6.0	NA	63.0	55.4	-47.3	63.5
action5	9.0	75.0	NA	10.0	-68.0	88.0
action4	2.0	54.9	23.0	83.5	-35.7	37.5
action1	4.0	22.5	41.0	71.0	-52.2	63.0

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation
Outranking model: **standard**, Ranking rule: **NetFlows**

Ordinal (Kendall) correlation between global ranking and global outranking relation: **+0.920**
Mean marginal correlation (a) : **+0.206**

Standard marginal correlation deviation (b) : **+0.286**

Ranking fairness (a) - (b) : **-0.081**

It might be opportune to furthermore study the robustness of the apparent outranking situations when assuming only *ordinal* or *uncertain* criteria significance weights. If interested in mainly objectively *unopposed* (multipartisan) outranking situations, one might also try the `UnOpposedOutrankingDigraph` constructor. (see the advanced topics of the `Digraph3` documentation).

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2.3 Generating random performance tableaux with the `randPerfTabs` module

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- [Random standard performance tableaux](#) (page 67)
- [Random Cost-Benefit performance tableaux](#) (page 70)
- [Random three objectives performance tableaux](#) (page 74)
- [Random academic performance tableaux](#) (page 78)
- [Random linearly ranked performance tableaux](#) (page 82)

Introduction

The `randomPerfTabs` module provides several constructors for generating random performance tableaux models of different kind, mainly for the purpose of testing implemented methods and tools presented and discussed in the Algorithmic Decision Theory course at the University of Luxembourg. This tutorial concerns the most useful models.

The simplest model, called **RandomPerformanceTableau**, generates a set of n decision actions, a set of m real-valued performance criteria, ranging by default from 0.0 to 100.0, associated with default discrimination thresholds: 2.5 (ind.), 5.0 (pref.) and 60.0 (veto). The generated performances are Beta(2.2) distributed on each measurement scale.

One of the most useful models, called **RandomCBPerformanceTableau**, proposes a performance tableau involving two decision objectives, named *Costs* (to be minimized) respectively *Benefits* (to be maximized); its purpose being to generate more or less contradictory performances on these two, usually conflicting, objectives. *Low costs* will randomly be coupled with *low benefits*, whereas *high costs* will randomly be coupled with high benefits.

Many public policy decision problems involve three often conflicting decision objectives taking into account *economical*, *societal* as well as *environmental* aspects. For this type of performance tableau model, we provide a specific model, called **Random3ObjectivesPerformanceTableau**.

Deciding which students, based on the grades obtained in a number of examinations, validate or not their academic studies, is the common decision practice of universities and academies. To thoroughly study these kind of decision problems, we provide a corresponding performance tableau model, called **RandomAcademicPerformanceTableau**, which gathers grades obtained by a given number of students in a given number of weighted courses.

In order to study aggregation of election results (see the tutorial on *Computing the winner of an election with the votingProfiles module* (page 129)) in the context of bipolar-valued outranking digraphs, we provide furthermore a specific performance tableau model called **RandomRankPerformanceTableau** which provides ranks (linearly ordered performances without ties) of a given number of election candidates (decision actions) for a given number of weighted voters (performance criteria).

Random standard performance tableaux

The `RandomPerformanceTableau` class, the simplest of the kind, specializes the generic `PerformanceTableau` class, and takes the following parameters.

- `numberOfActions` := nbr of decision actions.
- `numberOfCriteria` := number performance criteria.
- `weightDistribution` := ‘random’ (default) | ‘fixed’ | ‘equisignificant’:

If ‘random’, weights are uniformly selected randomly from the given weight scale;
If ‘fixed’, the `weightScale` must provided a corresponding weights distribution;

If ‘equisignificant’, all criterion weights are put to unity.

- weightScale := [Min,Max] (default =(1,numberOfCriteria)).
- IntegerWeights := True (default) | False (normalized to proportions of 1.0).
- commonScale := [a,b]; common performance measuring scales (default = [0.0,100.0])
- commonThresholds := [(q0,q1),(p0,p1),(v0,v1)]; common indifference(q), preference (p) and considerable performance difference discrimination thresholds. For each threshold type x in $\{q,p,v\}$, the float x_0 value represents a constant percentage of the common scale and the float x_1 value a proportional value of the actual performance measure. Default values are [(2.5.0,0.0),(5.0,0.0),(60.0,0,0)].
- commonMode := common random distribution of random performance measurements (default = ('beta',None,(2,2))):
 - (‘uniform’,None,None), uniformly distributed float values on the given common scales’ range [Min,Max].
 - (‘normal’,*mu*,*sigma*), truncated Gaussian distribution, by default $mu = (b-a)/2$ and $sigma = (b-a)/4$.
 - (‘triangular’,*mode*,*repartition*), generalized triangular distribution with a probability repartition parameter specifying the probability mass accumulated until the mode value. By default, $mode = (b-a)/2$ and $repartition = 0.5$.
 - (‘beta’,None,(alpha,beta)), a beta generator with default alpha=2 and beta=2 parameters.
- valueDigits := <integer>, precision of performance measurements (2 decimal digits by default).
- missingDataProbability := 0 <= float <= 1.0 ; probability of missing performance evaluation on a criterion for an alternative (default 0.025).
- NA := <Decimal> (default = -999); missing data symbol.

Code example.

Listing 2.14: Generating a random performance tableau

```

1  >>> from randomPerfTabs import RandomPerformanceTableau
2  >>> t = RandomPerformanceTableau(numberOfActions=21,numberOfCriteria=13,
3  <seed=100>
4  >>> t.actions
5      {'a01': {'comment': 'RandomPerformanceTableau() generated.',
6          'name': 'random decision action'},
7      'a02': { ... },
8      ...
9      }
10 >>> t.criteria
11     {'g01': {'thresholds': {'ind' : (Decimal('10.0'), Decimal('0.0'))},
12             (continues on next page)

```

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```

11             'veto': (Decimal('80.0'), Decimal('0.0')),
12             'pref': (Decimal('20.0'), Decimal('0.0'))},
13             'scale': [0.0, 100.0],
14             'weight': Decimal('1'),
15             'name': 'digraphs.RandomPerformanceTableau() instance',
16             'comment': 'Arguments: ; weightDistribution=random;
17                         weightScale=(1, 1); commonMode=None'},
18             'g02': { ... },
19             ...
20         }
21
22 >>> t.evaluation
23 {'g01': {'a01': Decimal('15.17'),
24           'a02': Decimal('44.51'),
25           'a03': Decimal('-999'), # missing evaluation
26           ...
27       },
28       ...
29 >>> t.showHTMLPerformanceTableau()

```

Performance table randomperftab

criteria	g01	g02	g03	g04	g05	g06	g07	g08	g09	g10	g11	g12	g13
weight	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
a01	15.17	46.37	82.88	41.14	59.94	41.19	58.68	44.73	22.19	64.64	34.93	42.36	17.55
a02	44.51	16.22	41.66	53.58	31.39	65.22	71.96	57.84	78.08	77.37	8.30	63.41	61.55
a03	NA	21.53	12.82	56.93	26.80	48.03	54.35	62.42	94.27	73.57	71.11	21.81	56.90
a04	58.00	51.16	21.92	65.57	59.02	44.77	37.49	58.39	80.79	55.39	46.44	19.57	39.22
a05	24.22	77.01	75.74	83.87	40.85	8.55	85.44	67.34	57.40	39.08	64.83	29.37	96.39
a06	29.10	39.35	15.45	34.99	49.12	11.49	28.44	52.89	64.24	62.92	58.28	32.02	10.25
a07	96.58	32.06	6.05	49.56	NA	66.06	41.64	13.08	38.31	24.82	48.39	57.03	42.91
a08	82.29	47.67	9.96	79.43	29.45	84.17	31.99	90.88	39.58	50.78	61.88	44.40	48.26
a09	43.90	14.81	60.55	42.37	6.72	56.14	34.20	51.54	21.79	79.13	50.95	93.16	81.89
a10	38.75	79.70	27.88	42.39	71.88	66.09	58.33	58.88	17.10	44.25	48.73	30.63	52.73
a11	35.84	67.48	38.81	33.75	26.87	64.10	71.95	62.72	NA	85.80	58.37	49.33	NA
a12	29.12	13.97	67.45	38.60	48.30	11.87	NA	57.76	74.86	26.57	48.80	43.57	7.68
a13	34.79	90.72	38.93	57.38	64.14	97.86	91.16	43.80	33.68	38.98	28.87	63.36	60.03
a14	62.22	80.16	19.26	62.34	60.96	24.72	73.63	71.21	56.43	46.12	26.09	51.43	12.86
a15	44.23	69.62	94.95	34.95	63.46	52.97	98.84	78.74	36.64	65.12	22.46	55.52	68.79
a16	19.10	45.49	65.63	64.96	50.57	55.91	10.02	34.70	29.31	50.15	70.68	62.57	71.09
a17	27.73	22.03	48.00	79.38	23.35	74.03	58.74	59.42	50.95	82.27	49.20	43.27	38.61
a18	41.46	33.83	7.97	75.11	49.00	55.70	64.99	38.47	49.86	17.45	28.08	35.21	67.81
a19	22.41	NA	34.86	49.30	65.18	39.84	81.16	NA	55.99	66.55	55.38	43.08	29.72
a20	21.52	69.98	71.81	43.74	24.53	55.39	52.67	13.67	66.80	57.46	70.81	5.41	76.05
a21	56.90	48.80	31.66	15.31	40.57	58.14	70.19	67.23	61.10	31.04	60.72	22.39	70.38

Fig. 2.9: Browser view on random performance tableau instance

Note

Missing (NA) evaluation are registered in a performance tableau by default as `Decimal(-999)` value (see Listing 2.14 Line 24). Best and worst performance on each criterion are marked in *light green*, respectively in *light red*.

Random Cost-Benefit performance tableaux

We provide the `RandomCBPerformanceTableau` class for generating random *Cost* versus *Benefit* organized performance tableaux following the directives below:

- We distinguish three types of decision actions: *cheap*, *neutral* and *expensive* ones with an equal proportion of 1/3. We also distinguish two types of weighted criteria: *cost* criteria to be *minimized*, and *benefit* criteria to be *maximized*; in the proportions 1/3 respectively 2/3.
- Random performances on each type of criteria are drawn, either from an ordinal scale [0;10], or from a cardinal scale [0.0;100.0], following a parametric triangular law of mode: 30% performance for cheap, 50% for neutral, and 70% performance for expensive decision actions, with constant probability repartition 0.5 on each side of the respective mode.
- Cost criteria use mostly cardinal scales (3/4), whereas benefit criteria use mostly ordinal scales (2/3).
- The sum of weights of the cost criteria by default equals the sum weights of the benefit criteria: `weighDistribution = 'equiobjectives'`.
- On cardinal criteria, both of cost or of benefit type, we observe following constant preference discrimination quantiles: 5% indifferent situations, 90% strict preference situations, and 5% considerable performance differences.

Parameters:

- If `numberOfActions` is *None*, a uniform random number between 10 and 31 of cheap, neutral or advantageous actions (equal 1/3 probability each type) actions is instantiated, otherwise a minimal integer greater than 5 is required
- If `numberOfCriteria` is *None*, a uniform random number between 5 and 21 of cost or benefit criteria (1/3 respectively 2/3 probability) is instantiated, otherwise a positive integer is required
- `weightDistribution := {'equiobjectives'|'fixed'|'random'|'equisignificant'}` (default = '`equisignificant`')
 - Default `weightScale` for '`random`' `weightDistribution` is $1 - \text{numberOfCriteria}$
 - All *cardinal* criteria are evaluated with decimals between 0.0 and 100.0 whereas *ordinal* criteria are evaluated with integers between 0 and 10
 - `commonPercentiles := {'ind':5, 'pref':10, 'veto':95}` (default) are expressed in percents (reversed for vetoes) and only concern cardinal criteria.

- *missingDataProbability* := 0 <= float <= 1.0 ; probability of missing performance evaluation on a criterion for an alternative (default 0.025).
- NA := <Decimal> (default = -999); missing data symbol.

Warning

Minimal number of decision actions required is 6 !

Example Python session

Listing 2.15: Generating a random Cost-Benefit performance tableau

```

1  >>> from randomPerfTabs import RandomCBPerformanceTableau
2  >>> t = RandomCBPerformanceTableau(
3  ...     numberOfActions=7,
4  ...     numberOfCriteria=5,
5  ...     weightDistribution='equiobjectives',
6  ...     commonPercentiles={'ind':0.05,'pref':0.10,'veto':0.95},
7  ...     seed=100)
8
9  >>> t.showActions()
10 *----- show decision action -----*
11 key: a1
12     short name: a1c
13     name:      random cheap decision action
14 key: a2
15     short name: a2n
16     name:      random neutral decision action
17 ...
18 key: a7a
19     short name: a7
20     name:      random advantageous decision action
21 >>> t.showCriteria()
22 *---- criteria ----*
23 c1 random cardinal cost criterion
24     Preference direction: min
25     Scale = (0.00, 100.00)
26     Weight = 0.167
27     Threshold ind : 2.33 + 0.00x ; percentile: 4.76
28     Threshold pref : 4.46 + 0.00x ; percentile: 14.29
29     Threshold veto : 64.23 + 0.00x ; percentile: 95.24
30 c2 'random cardinal cost criterion'
31 ...
32 c3 'random cardinal cost criterion'
33 ...

```

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```
34 b1 random ordinal benefit criterion
35 Preference direction: max
36 Scale = (0.00, 10.00)
37 Weight = 0.250
38 b2 random cardinal benefit criterion
39 ...
```

In the example above, we may notice the three types of decision actions (Listing 2.15 Lines 10-20), as well as the two types (Lines 22-32) of criteria with either an **ordinal** or a **cardinal** performance measuring scale. In the latter case, by default about 5% of the random performance differences will be below the **indifference** and 10% below the **preference discriminating threshold**. About 5% will be considered as **considerably large**. More statistics about the generated performances is available as follows.

```
1 >>> t.showStatistics()
2 ----- Performance tableau summary statistics -----
3 Instance name      : randomCBperftab
4 #Actions          : 7
5 #Criteria         : 5
6 Criterion name    : b1
7 Criterion weight   : 3
8 criterion scale    : 0.00 - 10.00
9 missing evaluations : 0
10 mean evaluation    : 4.43
11 standard deviation  : 2.50
12 maximal evaluation   : 9.00
13 quantile Q3 (x_75)   : 7.50
14 median evaluation    : 4.00
15 quantile Q1 (x_25)   : 2.75
16 minimal evaluation   : 2.00
17 mean absolute difference : 2.69
18 standard difference deviation : 3.53
19 ...
20 Criterion name    : c1
21 Criterion weight   : 2
22 criterion scale    : -100.00 - 0.00
23 missing evaluations : 0
24 mean evaluation    : -54.18
25 standard deviation  : 24.82
26 maximal evaluation   : 0.00
27 quantile Q3 (x_75)   : -25.36
28 median evaluation    : -48.33
29 quantile Q1 (x_25)   : -77.81
30 minimal evaluation   : -81.69
31 mean absolute difference : 27.62
32 standard difference deviation : 35.11
33 ...
```

A *Copeland* ranked colored heatmap with 5 color levels is also provided.

```
>>> t.showHTMLPerformanceHeatmap(colorLevels=5,Correlations=True,
... rankingRule='Copeland')
```

Heatmap of Performance Tableau'

criteria	b1	c2	c1	b2	c3
weights	+3.00	+2.00	+2.00	+3.00	+2.00
tau(*)	+0.62	+0.40	+0.31	-0.02	-0.26
a6n	9.00	-58.08	-39.33	52.77	-71.82
a5a	7.00	-39.65	-57.33	35.23	-43.45
a2n	3.00	-52.85	-15.47	47.34	-44.47
a7a	5.00	-34.87	-79.57	92.47	-87.54
a4c	2.00	-57.77	-77.23	69.06	-34.80
a1c	2.00	-79.26	-28.65	20.66	-3.19
a3n	3.00	-77.77	-81.69	57.44	-66.35

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between

marginal criterion and global ranking relation

Outranking model: standard, Ranking rule: Copeland

Ordinal (Kendall) correlation between

global ranking and global outranking relation: +0.728

Mean marginal correlation (a) : +0.224

Standard marginal correlation deviation (b) : +0.317

Ranking fairness (a) - (b) : -0.093

Fig. 2.10: Ranked heatmap of a random Cost-Benefit performance tableau

Such a performance tableau may be stored and re-accessed as follows.

```
1 >>> t.save('temp')
2     ----- saving performance tableau in XMCDA 2.0 format -----
3 File: temp.py saved !
4 >>> from perfTabs import PerformanceTableau
5 >>> t = PerformanceTableau('temp')
```

If needed –for instance in an R session– a CSV version of the performance tableau may be created as follows.

```
1 >>> t.saveCSV('temp')
2 * --- Storing performance tableau in CSV format in file temp.csv
```

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Random three objectives performance tableaux

We provide the `Random3ObjectivesPerformanceTableau` class for generating random performance tableaux concerning potential public policies evaluated with respect to three preferential decision objectives taking respectively into account *economical*, *societal* as well as *environmental* aspects.

Each public policy is qualified randomly as performing **weak** (-), **fair** (~) or **good** (+) on each of the three objectives.

Generator directives are the following:

- `numberOfActions` = 20 (default),
- `numberOfCriteria` = 13 (default),
- `weightDistribution` = ‘equiobjectives’ (default) | ‘random’ | ‘equisignificant’,
- `weightScale` = (1,`numberOfCriteria`): only used when random criterion weights are requested,
- `integerWeights` = True (default): False gives normalized rational weights,
- `commonScale` = (0.0,100.0),
- `commonThresholds` = [(5.0,0.0),(10.0,0.0),(60.0,0.0)]: Performance discrimination thresholds may be set for ‘ind’, ‘pref’ and ‘veto’,
- `commonMode` = [‘triangular’,‘variable’,0.5]: random number generators of various other types (‘uniform’,‘beta’) are available,
- `valueDigits` = 2 (default): evaluations are encoded as Decimals,
- `missingDataProbability` = 0.05 (default): random insertion of missing values with given probability,
- NA := <Decimal> (default = -999); missing data symbol.
- `seed`= None.

Note

If the mode of the **triangular** distribution is set to ‘variable’, three modes at 0.3 (-), 0.5 (~), respectively 0.7 (+) of the common scale span are set at random for each coalition and action.

Warning

Minimal number of decision actions required is 3 !

Example Python session

Listing 2.16: Generating a random 3 Objectives performance tableau

```

1  >>> from randomPerfTabs import Random3ObjectivesPerformanceTableau
2  >>> t = Random3ObjectivesPerformanceTableau(
3      ...         numberOfActions=31,
4      ...         numberOfCriteria=13,
5      ...         weightDistribution='equiobjectives',
6      ...         seed=120)
7
8  >>> t.showObjectives()
9      ----- show objectives -----
10     Eco: Economical aspect
11     ec04 criterion of objective Eco 20
12     ec05 criterion of objective Eco 20
13     ec08 criterion of objective Eco 20
14     ec11 criterion of objective Eco 20
15     Total weight: 80.00 (4 criteria)
16     Soc: Societal aspect
17     so06 criterion of objective Soc 16
18     so07 criterion of objective Soc 16
19     so09 criterion of objective Soc 16
20     s010 criterion of objective Soc 16
21     s013 criterion of objective Soc 16
22     Total weight: 80.00 (5 criteria)
23     Env: Environmental aspect
24     en01 criterion of objective Env 20
25     en02 criterion of objective Env 20
26     en03 criterion of objective Env 20
27     en12 criterion of objective Env 20
28     Total weight: 80.00 (4 criteria)

```

In Listing 2.16 above, we notice that 5 *equisignificant* criteria (g06, g07, g09, g10, g13) evaluate for instance the performance of the public policies from a **societal** point of view (Lines 16-22). 4 *equisignificant* criteria do the same from an **economical** (Lines 10-15), respectively an **environmental** point of view (Lines 23-28). The *equiobjectives* directive results hence in a balanced total weight (80.00) for each decision objective.

```

1  >>> t.showActions()
2  key: p01
3      name:      random public policy Eco+ Soc- Env+
4      profile:   {'Eco': 'good', 'Soc': 'weak', 'Env': 'good'}
5  key: p02
6  ...
7  key: p26
8      name:      random public policy Eco+ Soc+ Env-
9      profile:   {'Eco': 'good', 'Soc': 'good', 'Env': 'weak'}

```

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```

10 ...
11 key: p30
12 name: random public policy Eco- Soc- Env-
13 profile: {'Eco': 'weak', 'Soc': 'weak', 'Env': 'weak'}
14 ...

```

Variable triangular modes (0.3, 0.5 or 0.7 of the span of the measure scale) for each objective result in different performance status for each public policy with respect to the three objectives. Policy *p01*, for instance, will probably show *good* performances wrt the *economical* and environmental aspects, and *weak* performances wrt the *societal* aspect.

For testing purposes we provide a special `PartialPerformanceTableau` class for extracting a **partial performance tableau** from a given tableau instance. In the example blow, we may construct the partial performance tableaux corresponding to each one of the three decision objectives.

```

1 >>> from perfTabs import PartialPerformanceTableau
2 >>> teco = PartialPerformanceTableau(t,criteriaSubset=\
3 ...                               t.objectives['Eco']['criteria'])
4
5 >>> tsoc = PartialPerformanceTableau(t,criteriaSubset=\
6 ...                               t.objectives['Soc']['criteria'])
7
8 >>> tenv = PartialPerformanceTableau(t,criteriaSubset=\
9 ...                               t.objectives['Env']['criteria'])

```

One may thus compute a partial bipolar-valued outranking digraph for each individual objective.

```

1 >>> from outrankingDigraphs import BipolarOutrankingDigraph
2 >>> geco = BipolarOutrankingDigraph(teco)
3 >>> gsoc = BipolarOutrankingDigraph(tsoc)
4 >>> genv = BipolarOutrankingDigraph(tenv)

```

The three partial digraphs: *geco*, *gsoc* and *genv*, hence model the preferences represented in each one of the partial performance tableaux. And, we may aggregate these three outranking digraphs with an epistemic fusion operator.

```

1 >>> from digraphs import FusionLDigraph
2 >>> gfus = FusionLDigraph([geco,gsoc,genv])
3 >>> gfus.strongComponents()
4 {frozenset({'p30'}),
5  frozenset({'p10', 'p03', 'p19', 'p08', 'p07', 'p04', 'p21', 'p20',
6             'p13', 'p23', 'p16', 'p12', 'p24', 'p02', 'p31', 'p29',
7             'p05', 'p09', 'p28', 'p25', 'p17', 'p14', 'p15', 'p06',
8             'p01', 'p27', 'p11', 'p18', 'p22'})},
9 frozenset({'p26'})}

```

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```
10 >>> from digraphs import StrongComponentsCollapsedDigraph
11 >>> scc = StrongComponentsCollapsedDigraph(gfus)
12 >>> scc.showActions()
13     ----- show digraphs actions -----
14 key: frozenset({'p30'})
15     short name: Scc_1
16     name: _p30_
17     comment: collapsed strong component
18 key: frozenset({'p10', 'p03', 'p19', 'p08', 'p07', 'p04', 'p21', 'p20',
19   ↪ 'p13',
20           'p23', 'p16', 'p12', 'p24', 'p02', 'p31', 'p29', 'p05',
21   ↪ 'p09', 'p28', 'p25',
22           'p17', 'p14', 'p15', 'p06', 'p01', 'p27', 'p11', 'p18',
23   ↪ 'p22'}) 
24     short name: Scc_2
25     name: _p10_p03_p19_p08_p07_p04_p21_p20_p13_p23_p16_p12_p24_p02_
26   ↪ p31 \
27           p29_p05_p09_p28_p25_p17_p14_p15_p06_p01_p27_p11_p18_p22_
28     comment: collapsed strong component
29 key: frozenset({'p26'})
30     short name: Scc_3
31     name: _p26_
32     comment: collapsed strong component
```

A graphviz drawing illustrates the apparent preferential links between the strong components.

```
1 >>> scc.exportGraphViz('scFusionObjectives')
2     ----- exporting a dot file for GraphViz tools -----
3     Exporting to scFusionObjectives.dot
4     dot -Grankdir=BT -Tpng scFusionObjectives.dot -o scFusionObjectives.png
```

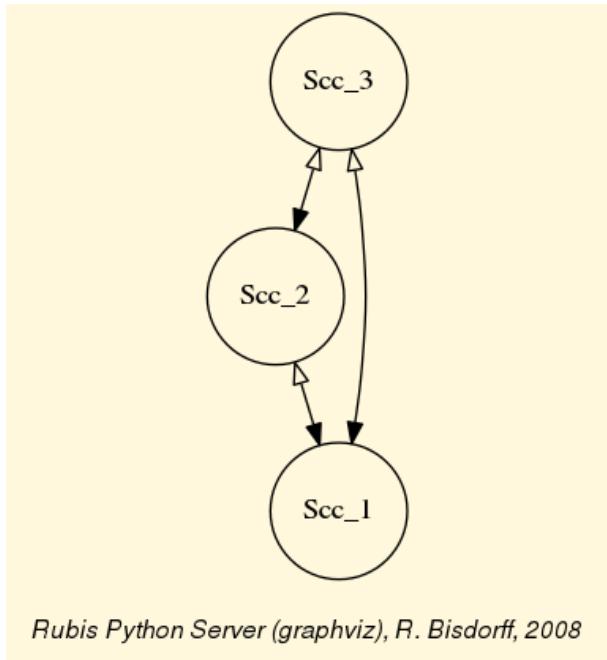


Fig. 2.11: Strong components digraph

Public policy $p26$ (Eco+ Soc+ Env-) appears dominating the other policies, whereas policy $p30$ (Eco- Soc- Env-) appears to be dominated by all the others.

Random academic performance tableaux

The `RandomAcademicPerformanceTableau` class generates temporary performance tableaux with random grades for a given number of students in different courses (see Lecture 4: *Grading*, Algorithmic decision Theory Course <http://hdl.handle.net/10993/37933>)

Parameters:

- number of students,
- number of courses,
- weightDistribution := ‘equisignificant’ | ‘random’ (default)
- weightScale := (1, 1 | numberOfCourses (default when random))
- IntegerWeights := Boolean (True = default)
- commonScale := (0,20) (default)
- ndigits := 0
- WithTypes := Boolean (False = default)
- commonMode := (‘triangular’,xm=14,r=0.25) (default)
- commonThresholds := {‘ind’:(0,0), ‘pref’:(1,0)} (default)
- missingDataProbability := 0.0 (default)

- NA := <Decimal> (default = -999); missing data symbol.

When parameter *WithTypes* is set to *True*, the students are randomly allocated to one of the four categories: *weak* (1/6), *fair* (1/3), *good* (1/3), and *excellent* (1/3), in the bracketed proportions. In a default 0-20 grading range, the random range of a weak student is 0-10, of a fair student 4-16, of a good student 8-20, and of an excellent student 12-20. The random grading generator follows in this case a double triangular probability law with *mode* (*xm*) equal to the middle of the random range and *median repartition* (*r* = 0.5) of probability each side of the mode.

Listing 2.17: Generating a random academic performance tableau

```

1  >>> from randomPerfTabs import RandomAcademicPerformanceTableau
2  >>> t = RandomAcademicPerformanceTableau(
3  ...         number_of_students=11,
4  ...         number_of_courses=7, missing_data_probability=0.03,
5  ...         WithTypes=True, seed=100)
6
7  >>> t
8  *----- PerformanceTableau instance description -----*
9  Instance class      : RandomAcademicPerformanceTableau
10 Seed                 : 100
11 Instance name       : randstudPerf
12 # Actions            : 11
13 # Criteria           : 7
14 Attributes           : ['randomSeed', 'name', 'actions',
15                         'criteria', 'evaluation', 'weightPreorder']
16 >>> t.showPerformanceTableau()
17 *---- performance tableau ----*
18 Courses | 'm1'   'm2'   'm3'   'm4'   'm5'   'm6'   'm7'
19 ECTS    | 2      1      3      4      1      1      5
20 -----|-----
21 's01f'  | 12     13     15     08     16     06     15
22 's02g'  | 10     15     20     11     14     15     18
23 's03g'  | 14     12     19     11     15     13     11
24 's04f'  | 13     15     12     13     13     10     06
25 's05e'  | 12     14     13     16     15     12     16
26 's06g'  | 17     13     10     14     NA     15     13
27 's07e'  | 12     12     12     18     NA     13     17
28 's08f'  | 14     12     09     13     13     15     12
29 's09g'  | 19     14     15     13     09     13     16
30 's10g'  | 10     12     14     17     12     16     09
31 's11w'  | 10     10     NA     10     10     NA     08
32 >>> t.weightPreorder
33 [[ 'm2', 'm5', 'm6'], [ 'm1'], [ 'm3'], [ 'm4'], [ 'm7']]
```

The example tableau, generated for instance above with *missingDataProbability* = 0.03, *WithTypes* = *True* and *seed* = 100 (see Listing 2.17 Lines 2-5), results in a set of two

excellent ($s05, s07$), five good ($s02, s03, s06, s09, s10$), three fair ($s01, s04, s08$) and one weak ($s11$) student performances. Notice that six students get a grade below the course validating threshold 10 and we observe four missing grades (NA), two in course $m5$ and one in course $m3$ and course $m6$ (see Lines 21-31).

We may show a statistical summary of the students' grades obtained in the highest weighted course, namely $m7$, followed by a performance heatmap browser view showing a global ranking of the students' performances from best to weakest.

Listing 2.18: Student performance summary statistics per course

```
1 >>> t.showCourseStatistics('m7')
2 *----- Summary performance statistics -----*
3 Course name      : g7
4 Course weight    : 5
5 # Students       : 11
6 grading scale   : 0.00 - 20.00
7 # missing evaluations : 0
8 mean evaluation  : 12.82
9 standard deviation : 3.79
10 maximal evaluation : 18.00
11 quantile Q3 (x_75) : 16.25
12 median evaluation  : 14.00
13 quantile Q1 (x_25)  : 10.50
14 minimal evaluation : 6.00
15 mean absolute difference : 4.30
16 standard difference deviation : 5.35
17 >>> t.showHTMLPerformanceHeatmap(colorLevels=5,
18 ...                               pageTitle='Ranking the students')
```

Ranking the students

criteria	g7	g4	g3	g1	g2	g5	g6
weights	+5.00	+4.00	+3.00	+2.00	+1.00	+1.00	+1.00
s07e	17.00	18.00	12.00	12.00	12.00	NA	13.00
s02g	18.00	11.00	20.00	10.00	15.00	14.00	15.00
s09g	16.00	13.00	15.00	19.00	14.00	9.00	13.00
s05e	16.00	16.00	13.00	12.00	14.00	15.00	12.00
s06g	13.00	14.00	10.00	17.00	13.00	NA	15.00
s03g	11.00	11.00	19.00	14.00	12.00	15.00	13.00
s10g	9.00	17.00	14.00	10.00	12.00	12.00	16.00
s01f	15.00	8.00	15.00	12.00	13.00	16.00	6.00
s08f	12.00	13.00	9.00	14.00	12.00	13.00	15.00
s04f	6.00	13.00	12.00	13.00	15.00	13.00	10.00
s11w	8.00	10.00	NA	10.00	10.00	10.00	NA

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------

Fig. 2.12: Ranking the students with a performance heatmap view

The ranking shown here in Fig. 2.12 is produced with the default *NetFlows ranking rule* (page 91). With a mean marginal correlation of +0.361 (see Listing 2.19 Lines 17-) associated with a low standard deviation (0.248), the result represents a rather *fair weighted consensus* made between the individual courses' marginal rankings.

Listing 2.19: Consensus quality of the students's ranking

```

1  >>> from outrankingDigraphs import BipolarOutrankingDigraph
2  >>> g = BipolarOutrankingDigraph(t)
3  >>> t.showRankingConsensusQuality(g.computeNetFlowsRanking())
4  Consensus quality of ranking:
5  ['s07', 's02', 's09', 's05', 's06', 's03', 's10',
6  's01', 's08', 's04', 's11']
7  criterion (weight): correlation
8  -----
9  m7 (0.294): +0.727
10 m4 (0.235): +0.309
11 m2 (0.059): +0.291
12 m3 (0.176): +0.200
13 m1 (0.118): +0.109
14 m6 (0.059): +0.091
15 m5 (0.059): +0.073
16 Summary:
17   Weighted mean marginal correlation (a): +0.361

```

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18	Standard deviation (b)	: +0.248
19	Ranking fairness (a)-(b)	: +0.113

Random linearly ranked performance tableaux

Finally, we provide the `RandomRankPerformanceTableau` class for generating multiple criteria ranked performance tableaux, i.e. on each criterion, all decision action's evaluations appear linearly ordered without ties.

This type of random performance tableau is matching the `RandomLinearVotingProfile` class provided by the `votingProfiles` module.

Parameters:

- number of actions,
- number of performance criteria,
- weightDistribution := ‘equisignificant’ | ‘random’ (default, see [above](#),)
- weightScale := (1, 1 | `numberOfCriteria` (default when random)).
- integerWeights := Boolean (True = default)
- commonThresholds (default) := {
 ‘ind’: (0,0),
 ‘pref’: (1,0),
 ‘veto’: (`numberOfActions`,0)
} (default)

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2.4 Linearly ranking with multiple incommensurable criteria

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- [The Copeland ranking](#) (page 86)
- [The polarised Bachet ranking](#) (page 89)
- [The NetFlows ranking](#) (page 91)
- [The valued Bachet ranking](#) (page 92)
- [Optimal Kemeny rankings](#) (page 93)
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- [Kohler’s ranking-by-choosing rule](#) (page 99)
- [Tideman’s ranked-pairs rule](#) (page 101)

The ranking problem

We need to rank without ties a set X of items (usually decision alternatives) that are evaluated on multiple incommensurable performance criteria; yet, for which we may know their pairwise bipolar-valued *strict outranking* characteristics, i.e. $r(x \succsim y)$ for all x, y in X (see *The strict outranking digraph* (page 30) and [BIS-2013]).

Let us consider a didactic outranking digraph g generated from a random *Cost-Benefit performance tableau* (page 70) concerning 9 decision alternatives evaluated on 13 performance criteria. We may compute the corresponding *strict outranking digraph* with a *codual transform* (page 18) as follows.

Listing 2.20: Random bipolar-valued strict outranking relation characteristics

```

1 >>> from outrankingDigraphs import *
2 >>> t = RandomCBPerformanceTableau(numberOfActions=9,
3 ...                               number_of_criteria=13, seed=200)
4
5 >>> g = BipolarOutrankingDigraph(t, Normalized=True)
6 >>> gcd = ~(-g) # codual digraph
7 >>> gcd.showRelationTable(ReflexiveTerms=False)
8 * ---- Relation Table ----
9 r(>) | 'a1'  'a2'  'a3'  'a4'  'a5'  'a6'  'a7'  'a8'  'a9'
10 -----|-----
11 'a1' |   -  0.00 +0.10 -1.00 -0.13 -0.57 -0.23 +0.10 +0.00
12 'a2' | -1.00   -  0.00 +0.00 -0.37 -0.42 -0.28 -0.32 -0.12
13 'a3' | -0.10  0.00   - -0.17 -0.35 -0.30 -0.17 -0.17 +0.00
14 'a4' |  0.00  0.00 -0.42   - -0.40 -0.20 -0.60 -0.27 -0.30
15 'a5' | +0.13 +0.22 +0.10 +0.40   - +0.03 +0.40 -0.03 -0.07
16 'a6' | -0.07 -0.22 +0.20 +0.20 -0.37   - +0.10 -0.03 -0.07
17 'a7' | -0.20 +0.28 -0.03 -0.07 -0.40 -0.10   - +0.27 +1.00
18 'a8' | -0.10 -0.02 -0.23 -0.13 -0.37 +0.03 -0.27   - +0.03
19 'a9' |  0.00 +0.12 -1.00 -0.13 -0.03 -0.03 -1.00 -0.03   -

```

Some ranking rules will work on the associated **Condorcet Digraph**, i.e. the corresponding *strict median cut* polarised digraph.

Listing 2.21: Median cut polarised strict outranking relation characteristics

```

1 >>> ccd = PolarisedOutrankingDigraph(gcd,
2 ...                               level=g.valuation_domain['med'],
3 ...                               KeepValues=False, StrictCut=True)
4 >>> ccd.recodeValuation(ndigits=0)
5 >>> ccd.showRelationTable(ReflexiveTerms=False)
6 *---- Relation Table ----
7 r(>)_med | 'a1'  'a2'  'a3'  'a4'  'a5'  'a6'  'a7'  'a8'  'a9'
8 -----|-----

```

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9	'a1'		-	0	+1	-1	-1	-1	+1	0
10	'a2'		-1	-	+0	0	-1	-1	-1	-1
11	'a3'		-1	0	-	-1	-1	-1	-1	0
12	'a4'		0	0	-1	-	-1	-1	-1	-1
13	'a5'		+1	+1	+1	+1	-	+1	+1	-1
14	'a6'		-1	-1	+1	+1	-1	-	+1	-1
15	'a7'		-1	+1	-1	-1	-1	-1	+1	+1
16	'a8'		-1	-1	-1	-1	-1	+1	-1	-
17	'a9'		0	+1	-1	-1	-1	-1	-1	-

Unfortunately, such crisp median-cut *Condorcet* digraphs, associated with a given strict outranking digraph, present only exceptionally a linear ordering. Usually, pairwise majority comparisons do not even render a *complete* or, at least, a *transitive* partial order. There may even frequently appear *cyclic* outranking situations (see the tutorial on [linear voting profiles](#) (page 129)).

To estimate how *difficult* this ranking problem here may be, we may have a look at the corresponding strict outranking digraph *graphviz* drawing ([Page 7, 1](#)).

```

1 >>> gcd.exportGraphViz('rankingTutorial')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to rankingTutorial.dot
4 dot -Grankdir=BT -Tpng rankingTutorial.dot -o rankingTutorial.png

```

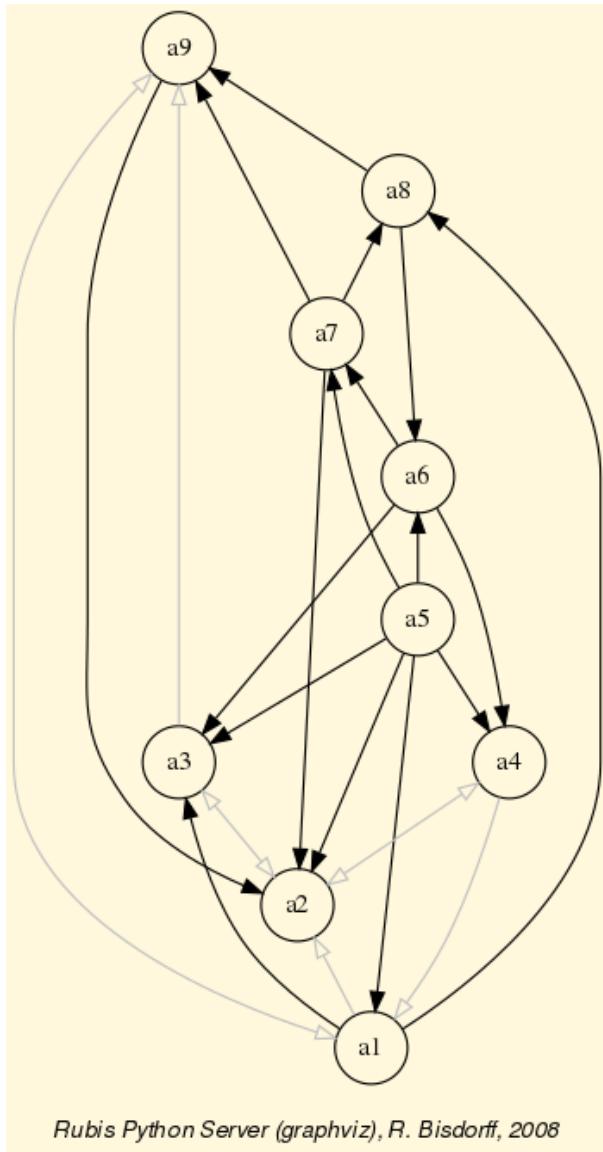


Fig. 2.13: The *strict outranking* digraph

The strict outranking relation \succ shown here is apparently *not transitive*: for instance, alternative a_8 outranks alternative a_6 and alternative a_6 outranks a_4 , however a_8 does not outrank a_4 (see Fig. 2.13). We may compute the transitivity degree of the outranking digraph, i.e. the ratio of the difference between the number of outranking arcs and the number of transitive arcs over the difference of the number of arcs of the transitive closure minus the transitive arcs of the digraph gcd .

```
>>> gcd.computeTransitivityDegree(Comments=True)
Transitivity degree of graph <codual_rel_randomCBperftab>
#triples x>y>z: 78, #closed: 38, #open: 40
#closed/#triples = 0.487
```

With only 49% of the required transitive triples, the strict outranking relation here is hence very far from being transitive; a serious problem when a linear ordering of the decision alternatives is looked for. Let us furthermore see if there are any cyclic outrank-

ings.

```

1 >>> gcd.computeChordlessCircuits()
2 >>> gcd.showChordlessCircuits()
3 1 circuit(s).
4 ----- Chordless circuits -----
5 1: ['a6', 'a7', 'a8'] , credibility : 0.033

```

There is one chordless circuit detected in the given strict outranking digraph gcd , namely a_6 outranks a_7 , the latter outranks a_8 , and a_8 outranks again a_6 (see Fig. 2.13). Any potential linear ordering of these three alternatives will, in fact, always contradict somehow the given outranking relation.

Now, several heuristic ranking rules have been proposed for constructing a linear ordering which is closest in some specific sense to a given outranking relation. The Digraph3 resources provide some of the most common of these ranking rules, like *Copeland's*, *Kemeny's*, *Slater's*, *Kohler's*, *Arrow-Raynaud's* or *Tideman's* ranking rule. Recently, new *Bachet* ranking rules have been added.

The *Copeland* ranking

Copeland's rule, the most intuitive one as it balances the outdegrees –the number of *outranking* situations– against the indegrees –the number of *outranked* situations, of the *median cut* polarised strict outranking digraph ccd . The rule computes for each alternative x a score resulting from the sum of the differences between the polarised **strict outranking** characteristics $r(x \succsim y)_{>0}$ and the polarised **strict outranked** characteristics $r(y \succsim x)_{>0}$ for all alternatives y different from x . The set of alternatives is eventually ranked in decreasing order of these *Copeland* scores; ties, the case given, being resolved by a lexicographical rule.

Listing 2.22: Computing a *Copeland* Ranking

```

1 >>> from linearOrders import CopelandRanking
2 >>> cop = CopelandRanking(gcd,Comments=True)
3 Copeland decreasing scores
4 a5 : 12
5 a1 : 2
6 a6 : 2
7 a7 : 2
8 a8 : 0
9 a4 : -3
10 a9 : -3
11 a3 : -5
12 a2 : -7
13 Copeland Ranking:
14 ['a5', 'a1', 'a6', 'a7', 'a8', 'a4', 'a9', 'a3', 'a2']

```

Alternative a_5 obtains here the best *Copeland* score (+12), followed by alternatives a_1 , a_6 and a_7 with same score (+2); following the lexicographic rule, a_1 is hence ranked before a_6 and a_6 before a_7 . Same situation is observed for a_4 and a_9 with a score of -3

(see Listing 2.22 Lines 4-12 and 14).

Copeland's ranking rule appears in fact **invariant** under the *codual transform* (page 18) and renders a same linear order indifferently from digraphs g or gcd . The *Copeland* rule is furthermore **Condorcet consistent**, i.e. when the strict outranking relation models a *transitive* relation, this relation is preserved in the *Copeland* ranking result.

The *Copeland* ranking result (see Listing 2.22 Line 14) is rather correlated (+0.463) with the given pairwise outranking relation in the ordinal *Kendall* sense (see Listing 2.23).

Listing 2.23: Checking the quality of the *Copeland* Ranking

```

1 >>> corr = g.computeRankingCorrelation(cop.copelandRanking)
2 >>> g.showCorrelation(corr)
3 Correlation indexes:
4   Crisp ordinal correlation : +0.463
5   Valued equivalence       : +0.107
6   Epistemic determination  :  0.230

```

With an epistemic determination level of 0.230, the *extended Kendall tau* index (see [BIS-2012]) is in fact computed on 61.5% ($100.0 \times (1.0 + 0.23)/2$) of the pairwise strict outranking comparisons. Furthermore, the bipolar-valued *relational equivalence* characteristics between the strict outranking relation and the *Copeland* ranking equals +0.107, i.e. a *majority* of 55.35% of the criteria significance supports the relational equivalence between the given strict outranking relation and the corresponding *Copeland* ranking⁵⁹.

The *Copeland* scores deliver actually only a unique *weak ranking*, i.e. a ranking with potential ties. This weak ranking may be constructed with the *transitiveDigraphs*.*WeakCopelandOrder* class.

Listing 2.24: Computing a weak *Copeland* ranking

```

1 >>> from transitiveDigraphs import WeakCopelandOrder
2 >>> wcop = WeakCopelandOrder(g)
3 >>> wcop.showRankingByChoosing()
4 Ranking by Choosing and Rejecting
5   1st ranked ['a5']
6   2nd ranked ['a1', 'a6', 'a7']
7   3rd ranked ['a8']
8   3rd last ranked ['a4', 'a9']
9   2nd last ranked ['a3']
10  1st last ranked ['a2']

```

We recover in Listing 2.24 Lines 6 and 8 above, the ranking with ties delivered by the *Copeland* scores (see Listing 2.22). We may draw its corresponding *Hasse* diagram (see Listing 2.25).

⁵⁹ See the advanced topic on bipolar-valued relational equivalence between bipolar-valued digraphs.

Listing 2.25: Drawing a weak *Copeland* ranking

```
1 >>> wcop.exportGraphViz(fileName='weakCopelandRanking')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to weakCopelandRanking.dot
4 subgraph { rank = same; a5; }
5 1 subgraph { rank = same; a1; a7; a6; }
6 2 subgraph { rank = same; a8; }
7 3 subgraph { rank = same; a4; a9}
8 4 subgraph { rank = same; a3; }
9 5 subgraph { rank = same; a2; }
10 dot -Grankdir=TB -Tpng weakCopelandRanking.dot\
11      -o weakCopelandRanking.png
```

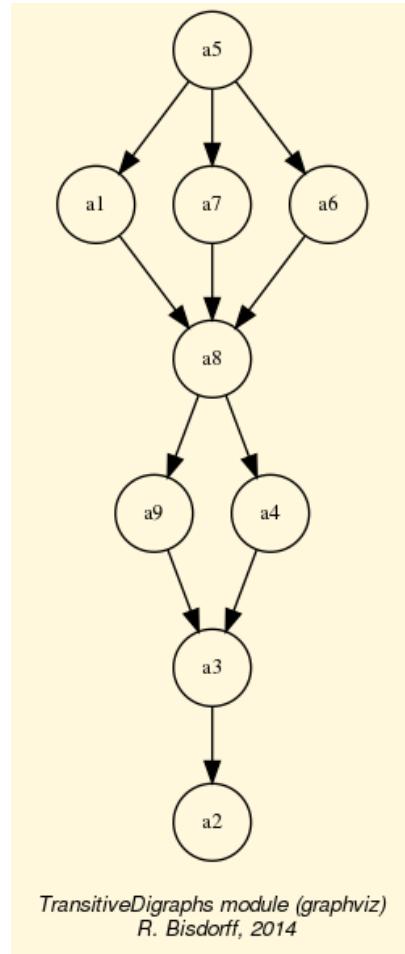


Fig. 2.14: A weak Copeland ranking

A similar ranking-by-scoring rule is provided by the `BachetRanking` class.

The polarised *Bachet* ranking

Bachet numbers –bipolar-valued $\{-1,0,+1\}$ base 3 encoded integers, provided by the `BachetInteger` class and instantiated by the row vectors and the column vectors –both without reflexive terms– of the strict outranking digraph’s polarised relation table, model in fact per decision action respectively an **outrankingness** and a **negated outrankedness** ranking fitness score similar to the previous *Copeland* ranking scores (see the advanced topic on a new ranking rule based on bipolar-valued base 3 Bachet numbers).

Now, *Bachet* numbers are formulated in a positional numbering system and the integer values of the *Bachet* ranking scores therefore depend on the actual ordering of the outranking digraph’s *actions* dictionary. The polarised `BachetRanking` rule is nevertheless **Condorcet consistent**, ie. when the outranking digraph models a transitive relation, this relation will be preserved by the polarised `BachetRanking` ranking scores. However, unlike the *Copeland* rule, the rule is **not invariant** under the **codual** transform⁶².

Here, as we have seen above, the given digraph’s transitivity degree is only 0.487. To reduce the dependency on the given initial ordering of the *actions* dictionary, we compute below *Bachet* ranking results for the permutation and their reversed ordering of its 40 intransitive triples (see Listing 2.26 Line 2) and keep the one ranking that is best correlated with the given outranking digraph (see `BachetRanking-rule-label`).

Listing 2.26: Computing a *Bachet* ranking

```

1  >>> from linearOrders import BachetRanking
2  >>> ba = BachetRanking(g,Polarised=True,sampleSize=40)
3  >>> ba.showScores()
4      Bachet scores in descending order
5      action      score
6      a5          +5084
7      a6          +4478
8      a7          +3954
9      a3          +79
10     a4          +75
11     a1          -22
12     a8          -3240
13     a9          -4411
14     a2          -6081
15  >>> ba.bachetRanking
16  ['a5', 'a6', 'a7', 'a3', 'a4', 'a1', 'a8', 'a9', 'a2']
17  >>> corr = g.computeRankingCorrelation(ba.bachetRanking)
18  >>> g.showCorrelation(corr)
19      Correlation indexes:
20      Crisp ordinal correlation : +0.767
21      Epistemic determination   : 0.230
22      Bipolar-valued equivalence : +0.177

```

In Listing 2.26 Line 20 above, we may observe that the *Bachet* scores lead eventually to

⁶² The set of intransitive triples of an outranking digraph g and its associated codual gcd , to be permuted in the search for a best qualified ranking result, are usually not the same.

a ranking result that is much better correlated with the given outranking relation than the previous *Copeland* ranking (+0.767 versus +0.463).

A heatmap view on the performance tableau illustrates the actual quality of this *Bachet* ranking result.

```

1 >>> g.showHTMLPerformanceHeatmap(Correlations=True,
2 ...           colorLevels=7,
3 ...           actionsList=ba.bachetRanking)

```

Heatmap of Performance Tableau 'rel_randomCBperftab'

criteria	b09	b04	b01	c01	b08	b02	b05	b07	b03	c02	b10	b06	c03
weights	+3.00	+3.00	+3.00	+10.00	+3.00	+3.00	+3.00	+3.00	+3.00	+10.00	+3.00	+3.00	+10.00
tau(*)	+0.47	+0.33	+0.32	+0.31	+0.29	+0.18	+0.11	+0.03	+0.00	+0.00	+0.00	-0.15	-0.17
a5c	9.00	8.00	14.90	-3.00	59.61	36.22	3.00	6.00	8.00	-4.00	5.00	63.82	-4.00
a6c	3.00	2.00	71.50	-2.00	45.96	44.52	7.00	2.00	2.00	-4.00	3.00	53.21	-5.00
a7a	8.00	6.00	74.93	-4.00	28.97	52.55	8.00	8.00	7.00	-5.00	6.00	74.93	-9.00
a3a	10.00	8.00	74.88	-8.00	74.15	40.73	5.00	8.00	8.00	-6.00	8.00	44.22	-7.00
a4a	7.00	3.00	56.50	-8.00	78.46	67.86	5.00	5.00	3.00	-5.00	8.00	86.83	-9.00
a1c	3.00	2.00	34.86	-2.00	28.16	85.03	2.00	1.00	2.00	-5.00	1.00	29.36	-1.00
a8n	6.00	8.00	56.83	-5.00	51.26	32.86	5.00	5.00	8.00	-8.00	8.00	63.30	-3.00
a9c	2.00	0.00	9.09	-8.00	46.35	18.86	3.00	7.00	9.00	-1.00	1.00	82.40	-2.00
a2c	3.00	2.00	33.38	-5.00	9.72	25.34	6.00	6.00	2.00	-2.00	NA	68.26	-5.00

Color legend:

quantile	14.29%	28.57%	42.86%	57.14%	71.43%	85.71%	100.00%
----------	--------	--------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between

marginal criterion and global ranking relation

Outranking model: standard, Ranking rule: None

Ordinal (Kendall) correlation between

global ranking and global outranking relation: +0.767

Mean marginal correlation (a) : +0.102

Standard marginal correlation deviation (b) : +0.198

Ranking fairness (a) - (b) : -0.096

Fig. 2.15: *Bachet* rule ranked heatmap view on the performance records

In Fig. 2.15 we may notice that action *a5*, with all grades above the third 7-tile ($> 42.86\%$), appears convincingly first-ranked. Similarly, with six grades in the two lowest 7-tiled classes ($< 28.57\%$), action *a2* appears last-ranked. Most significant in this ranking appear to be the *Benefit* criteria *b09*, *b04*, *b01*, *c01* and *b08* with a correlation $> +0.20$, whereas *Costs* criteria *c03* and *b05* appear somehow in contradiction (< -0.20) with the proposed *Bachet* ranking. Action *a7*, with only three weak grades, is not first-ranked because of the fact that on all three *Costs* criteria and on the *Benefit* criterion *b08*, i.e on a majority (33/60) of criteria significance, action *a7* is positively outranked by actions *a6* and *a5*. Notice also the highly contrasted performance record of action *a1* with three grades in the highest 7-tile ($> 85.71\%$) and four grades in the lowest 7-tile ($< 14.29\%$). A similar contrasted situation is given for action *a3* with 7 grades in the two top 7-tiles ($> 71.43\%$) and four grades in the two lowest 7-tiles ($< 28.57\%$). The mean marginal

correlation over all 13 criteria is slightly positive (+0.10). The standard deviation of the marginal correlations is a bit high (+0.198) so that the ranking may lack a bit of fairness (-0.096).

Let us now consider a similar ranking rule, but working directly on the *bipolar-valued* outranking digraph.

The *NetFlows* ranking

A further valued version of the *Copeland* rule, called **NetFlows** rule, computes for each alternative x a *net flow* score, i.e. the sum of the differences between the **strict outranking** characteristics $r(x \succsim y)$ and the **strict outranked** characteristics $r(y \succsim x)$ for all pairs of alternatives where y is different from x .

Listing 2.27: Computing a *NetFlows* ranking

```

1  >>> from linearOrders import NetFlowsRanking
2  >>> nf = NetFlowsRanking(gcd,Comments=True)
3  Net Flows :
4  a5 : 3.600
5  a7 : 2.800
6  a6 : 1.300
7  a3 : 0.033
8  a1 : -0.400
9  a8 : -0.567
10 a4 : -1.283
11 a9 : -2.600
12 a2 : -2.883
13 NetFlows Ranking:
14  ['a5', 'a7', 'a6', 'a3', 'a1', 'a8', 'a4', 'a9', 'a2']
15 >>> cop.copelandRanking
16  ['a5', 'a1', 'a6', 'a7', 'a8', 'a4', 'a9', 'a3', 'a2']
```

It is worthwhile noticing again that, similar to the *Copeland* ranking rule seen before, the *NetFlows* ranking rule is also **invariant** under the *codual transform* (page 18) and delivers again the same ranking result indifferently from digraphs g or gcd (see Listing 2.27 Line 14). Yet, the *NetFlows* ranking rule, working directly with the bipolar characteristic values of the outranking relation is **not** necessarily **Condorcet consistent**.

In our example here, the *NetFlows* scores deliver a ranking *without ties* which is rather different from the one delivered by *Copeland's* rule (see Listing 2.27 Line 16). It may happen, however, that we obtain, as with the *Copeland* scores above, only a ranking result with ties, which may then be resolved again by following a lexicographic rule. In such cases, it is possible to construct again a *weak ranking* with the corresponding **WeakNetFlowsOrder** class.

The **NetFlows** ranking result appears to be better correlated (+0.638) with the given outranking relation than its crisp cousin, the *Copeland* ranking (see Listing 2.23 Lines 4-6).

Listing 2.28: Checking the quality of the *NetFlows* Ranking

```

1 >>> corr = gcd.computeOrdinalCorrelation(nf)
2 >>> gcd.showCorrelation(corr)
3 Correlation indexes:
4   Extended Kendall tau      : +0.638
5   Epistemic determination    :  0.230
6   Bipolar-valued equivalence : +0.147

```

Indeed, the extended *Kendall* tau index of +0.638 leads to a bipolar-valued *relational equivalence* characteristics of +0.147, i.e. a *majority* of 57.35% of the criteria significance supports the relational equivalence between the given outranking digraphs *g* or *gcd* and the corresponding *NetFlows* ranking. The lesser ranking performance of the previous *Copeland* rule stems in this example here essentially from the *weakness* of the actual *Copeland* ranking result and our subsequent *arbitrary* lexicographic resolution of the many ties given by the *Copeland* scores (see Fig. 2.14).

The valued *Bachet* ranking

The polarised *Bachet* ranking rule only considers the crisp relational structure of the outranking digraph, ignoring the actual credibility of the individual outranking situations. The *BachetRanking* rule now provides the *Polarised=False* parameter for taking into account, like the *NetFlows* rule, the actual bipolar-valued characteristic determination of the outranking situations. The *Bachet* numbers making up the ranking scores are therefore instantiated from the rows and columns of the normalized relation instead of the polarised relation of the outranking digraph.

Listing 2.29: Computing a valued *Bachet* ranking

```

1 >>> from linearOrders import BachetRanking
2 >>> bav = BachetRanking(g,Polarised=False,sampleSize=40,
3 ...                      Randomized=True,seed=11)
4 >>> bav.showScores()
5 Bachet scores in descending order
6   action      score
7   a5          +1676
8   a6          +1492
9   a7           +712
10  a3            +370
11  a4             +74
12  a8            -120
13  a1            -269
14  a2            -286
15  a9           -2071
16 >>> bav.bachetRanking
17  ['a5', 'a6', 'a7', 'a3', 'a4', 'a8', 'a1', 'a2', 'a9']
18 >>> ba.bachetRanking

```

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```

19  ['a5', 'a6', 'a7', 'a3', 'a4', 'a1', 'a8', 'a9', 'a2']
20 >>> corr = g.computeRankingCorrelation(bav.bachetRanking)
21 >>> g.showCorrelation(corr)
22 Correlation indexes:
23   Crisp ordinal correlation : +0.715
24   Epistemic determination   : 0.230
25   Bipolar-valued equivalence: +0.165

```

With the *valued* version of the *Bachet* ranking rule we recover a similar ranking as the one obtained with the previous polarised version. We are randomly permuting the 40 intransitive triples (see Listing 2.29 Lines 2-3). This way we obtain a better correlated ranking result than with the simple *NetFlows* rule (+715 vs +0.638). The valued *BachetRanking* class result is, like the previous polarised *BachetRanking* class result **not** invariant under the **codual transform**^{Page 89, 62} and, like the *NetFlows* rule **not** necessarily **Condorcet consistent**.

To appreciate now the actual ranking performances of the *ranking-by-scoring* rules seen so far, it is useful to consider *Kemeny*'s and *Slater*'s **optimal fitting** ranking rules.

Optimal *Kemeny* rankings

A **Kemeny** ranking is a linear ranking without ties which is *closest*, in the sense of the ordinal (Kendall) correlation index (see the advanced topic on the bipolar-valued relational equivalence between bipolar-valued digraphs [BIS-2012]), to the given valued outranking digraphs *g* or *gcd*. This rule is also *invariant* under the *codual* transform, yet, not necessarily *Condorcet consistent*.

Listing 2.30: Computing a *Kemeny* ranking

```

1 >>> from linearOrders import KemenyRanking
2 >>> ke = KemenyRanking(gcd,orderLimit=9) # default orderLimit is 7
3 >>> ke.showRanking()
4  ['a5', 'a6', 'a7', 'a3', 'a9', 'a4', 'a1', 'a8', 'a2']
5 >>> corr = gcd.computeOrdinalCorrelation(ke)
6 >>> gcd.showCorrelation(corr)
7 Correlation indexes:
8   Extended Kendall tau      : +0.779
9   Epistemic determination   : 0.230
10  Bipolar-valued equivalence: +0.179

```

So, **+0.779** represents the *highest possible* ordinal correlation any potential linear ranking can achieve with the given pairwise outranking digraph (see Listing 2.30 Lines 7-10).

A *Kemeny* ranking may not be unique. In our example here, we obtain in fact two *Kemeny* rankings with a same **maximal** correlation of +0.779 (see [BIS-2012]).

Listing 2.31: Optimal *Kemeny* rankings

```
1 >>> ke.maximalRankings
2 [['a5', 'a6', 'a7', 'a3', 'a8', 'a9', 'a4', 'a1', 'a2'],
3 ['a5', 'a6', 'a7', 'a3', 'a9', 'a4', 'a1', 'a8', 'a2']]
```

We visualize the partial order defined by the *epistemic fusion* (page 17) of both optimal *Kemeny* rankings by using the `RankingsFusionDigraph` class as follows.

Listing 2.32: Computing the epistemic fusion of all optimal *Kemeny* rankings

```
1 >>> from transitiveDigraphs import RankingsFusionDigraph
2 >>> wke = RankingsFusionDigraph(ke,ke.maximalRankings)
3 >>> wke.exportGraphViz(fileName='tutorialKemeny')
4 *---- exporting a dot file for GraphViz tools ----*
5 Exporting to tutorialKemeny.dot
6 0 subgraph { rank = same; a5; }
7 1 subgraph { rank = same; a6; }
8 2 subgraph { rank = same; a7; }
9 3 subgraph { rank = same; a3; }
10 4 subgraph { rank = same; a9; a8; }
11 5 subgraph { rank = same; a4; }
12 6 subgraph { rank = same; a1; }
13 7 subgraph { rank = same; a2; }
14 dot -Grankdir=TB -Tpng tutorialKemeny.dot -o tutorialKemeny.png
```

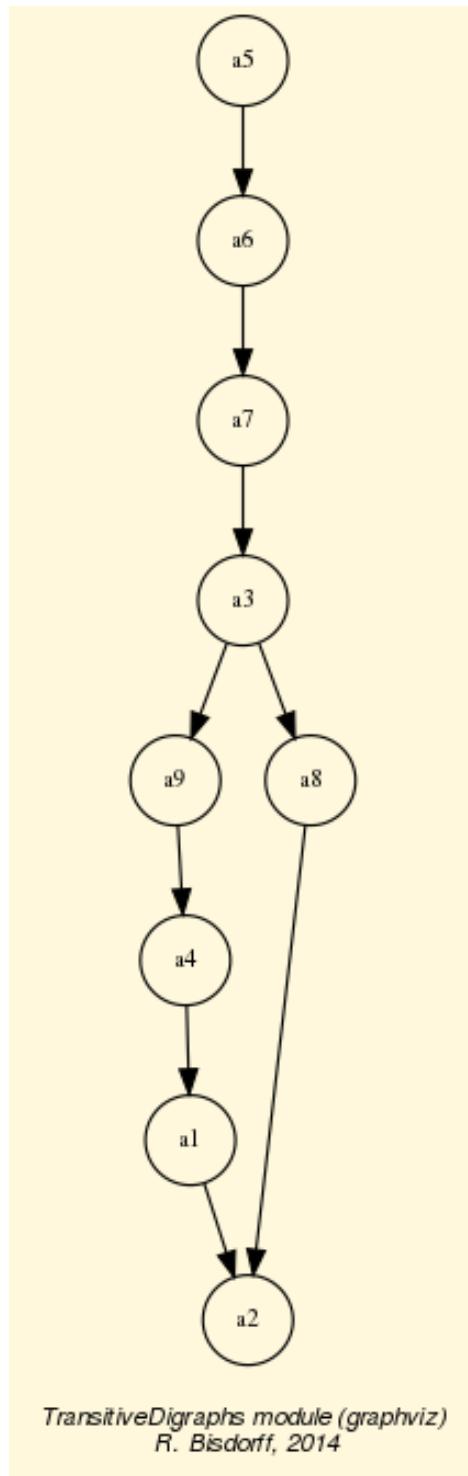


Fig. 2.16: Epistemic disjunctive fusion of optimal *Kemeny* rankings

It is interesting to notice in Fig. 2.16 and Listing 2.31, that both *Kemeny* rankings only differ in their respective positioning of alternative a_8 ; either before or after alternatives a_9 , a_4 and a_1 .

To choose now a specific representative among all the potential rankings with maximal ordinal correlation index, we will choose, with the help of the `showRankingConsensusQuality()` method, the *most consensual* one.

Listing 2.33: Computing Consensus Quality of Rankings

```
1 >>> g.showRankingConsensusQuality(ke.maximalRankings[0])
2 Consensus quality of ranking:
3   ['a5', 'a6', 'a7', 'a3', 'a8', 'a9', 'a4', 'a1', 'a2']
4 criterion (weight): correlation
5 -----
6   b09 (0.050): +0.361
7   b04 (0.050): +0.333
8   b08 (0.050): +0.292
9   b01 (0.050): +0.264
10  c01 (0.167): +0.250
11  b03 (0.050): +0.222
12  b07 (0.050): +0.194
13  b05 (0.050): +0.167
14  c02 (0.167): +0.000
15  b10 (0.050): +0.000
16  b02 (0.050): -0.042
17  b06 (0.050): -0.097
18  c03 (0.167): -0.167
19 Summary:
20   Weighted mean marginal correlation (a): +0.099
21   Standard deviation (b) : +0.177
22   Ranking fairness (a)-(b) : -0.079
23 >>> g.showRankingConsensusQuality(ke.maximalRankings[1])
24 Consensus quality of ranking:
25   ['a5', 'a6', 'a7', 'a3', 'a9', 'a4', 'a1', 'a8', 'a2']
26 criterion (weight): correlation
27 -----
28   b09 (0.050): +0.306
29   b08 (0.050): +0.236
30   c01 (0.167): +0.194
31   b07 (0.050): +0.194
32   c02 (0.167): +0.167
33   b04 (0.050): +0.167
34   b03 (0.050): +0.167
35   b01 (0.050): +0.153
36   b05 (0.050): +0.056
37   b02 (0.050): +0.014
38   b06 (0.050): -0.042
39   c03 (0.167): -0.111
40   b10 (0.050): -0.111
41 Summary:
42   Weighted mean marginal correlation (a): +0.099
43   Standard deviation (b) : +0.132
44   Ranking fairness (a)-(b) : -0.033
```

Both Kemeny rankings show the same *weighted mean marginal correlation* (+0.099, see Listing 2.33 Lines 19-22, 42-44) with all thirteen performance criteria. However, the second ranking shows a slightly lower *standard deviation* (+0.132 vs +0.177), resulting in a slightly **fairer** ranking result (-0.033 vs -0.079).

When several rankings with maximal correlation index are given, the `KemenyRanking` class constructor instantiates a *most consensual* one, i.e. a ranking with *highest* mean marginal correlation and, in case of ties, with *lowest* weighted standard deviation. Here we obtain ranking: ['a5', 'a6', 'a7', 'a3', 'a9', 'a4', 'a1', 'a8', 'a2'] (see Listing 2.30 Line 4).

Let us now present the non-valued cousin of the optimal *Kemeny* rule.

Optimal *Slater* rankings

The **Slater** ranking rule is identical to *Kemeny*'s but works, instead, on the *median cut polarised* digraph. *Slater*'s ranking rule is also *invariant* under the *codual* transform and delivers again indifferently on g or gcd the following results.

Listing 2.34: Computing a *Slater* ranking

```

1 >>> from linearOrders import SlaterRanking
2 >>> sl = SlaterRanking(gcd,orderLimit=9)
3 >>> sl.slaterRanking
4   ['a5', 'a6', 'a4', 'a1', 'a3', 'a7', 'a8', 'a9', 'a2']
5 >>> corr = gcd.computeRankingCorrelation(sl.slaterRanking)
6 >>> sl.showCorrelation(corr)
7   Correlation indexes:
8     Extended Kendall tau      : +0.676
9     Epistemic determination   :  0.230
10    Bipolar-valued equivalence : +0.156
11 >>> len(sl.maximalRankings)
12   7

```

We notice in Listing 2.34 Line 7 that the first *Slater* ranking is a rather good fit (+0.676), slightly better apparently than the *NetFlows* ranking result (+0.638). However, there are in fact 7 such potentially optimal *Slater* rankings (see Listing 2.34 Line 11). The corresponding *epistemic fusion* (page 17) gives the following partial ordering.

Listing 2.35: Computing the epistemic disjunction of optimal *Slater* rankings

```

1 >>> slw = RankingsFusionDigraph(sl,sl.maximalRankings)
2 >>> slw.exportGraphViz(fileName='tutorialSlater')
3   ----- exporting a dot file for GraphViz tools -----
4   Exporting to tutorialSlater.dot
5   0 subgraph { rank = same; a5; }
6   1 subgraph { rank = same; a6; }
7   2 subgraph { rank = same; a7; a4; }
8   3 subgraph { rank = same; a1; }

```

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```

9 4 subgraph { rank = same; a8; a3; }
10 5 subgraph { rank = same; a9; }
11 6 subgraph { rank = same; a2; }
12 dot -Grankdir=TB -Tpng tutorialSlater.dot -o tutorialSlater.png

```

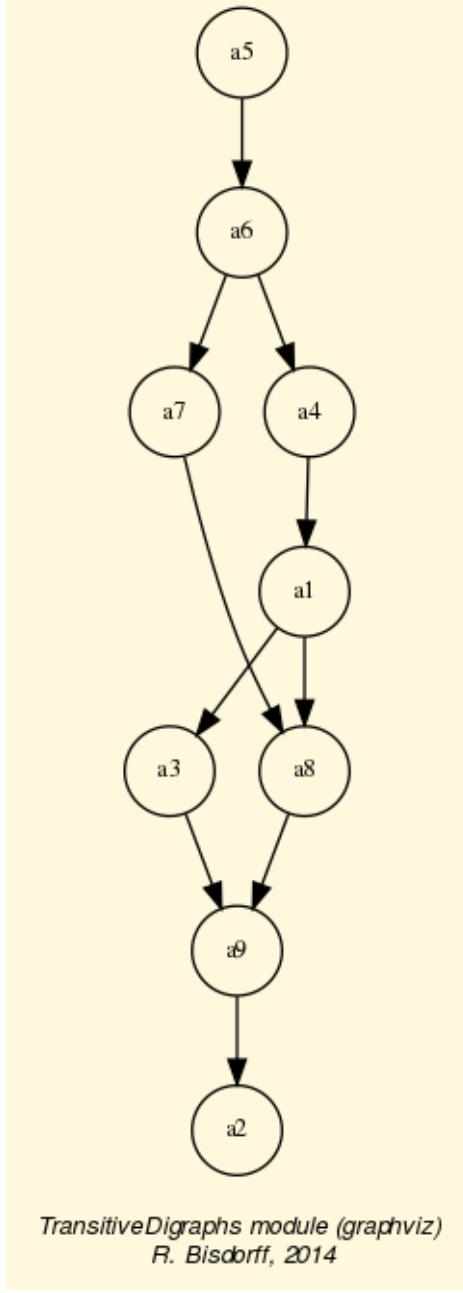


Fig. 2.17: Epistemic fusion of optimal *Slater* rankings

What precise ranking result should we hence adopt? With a complexity of $O(n!)$ where n is the order of the outranking digraph, *Kemeny's* and *Slater's* optimal ranking rules are computationally *difficult* problems and effective ranking results are only computable for small outranking digraphs (< 20 objects).

Efficient *ranking-by-scoring* heuristics, like the *Copeland* and the *NetFlows* rules with a complexity of $O(n^2)$ are therefore needed in practice.

Let us finally present two popular *ranking-by-choosing* strategies.

Kohler's ranking-by-choosing rule

Kohler's *ranking-by-choosing* rule can be formulated like this.

At step i (i goes from 1 to n) do the following:

1. Compute for each row of the bipolar-valued *strict outranking* relation table (see Listing 2.20) the smallest value;
2. Select the row where this minimum is maximal. Ties are resolved in lexicographic order;
3. Put the selected decision alternative at rank i ;
4. Delete the corresponding row and column from the relation table and restart until the table is empty.

Listing 2.36: Computing a *Kohler* ranking

```

1 >>> from linearOrders import KohlerRanking
2 >>> kocd = KohlerRanking(gcd)
3 >>> kocd.showRanking()
4   ['a5', 'a7', 'a6', 'a3', 'a9', 'a8', 'a4', 'a1', 'a2']
5 >>> corr = gcd.computeOrdinalCorrelation(kocd)
6 >>> gcd.showCorrelation(corr)
7 Correlation indexes:
8   Extended Kendall tau      : +0.747
9   Epistemic determination    :  0.230
10  Bipolar-valued equivalence : +0.172

```

With this *min-max* lexicographic *ranking-by-choosing* strategy, we find a correlation result (+0.747) that is until now the nearest to an optimal *Kemeny* ranking (see Listing 2.31). Only two adjacent pairs: $[a6, a7]$ and $[a8, a9]$ are actually inverted here. Notice that *Kohler's* ranking rule, contrary to the previously mentioned rules, is **not invariant** under the *codual* transform and requires to work on the *strict outranking* digraph *gcd* for a better correlation result.

```

1 >>> ko = KohlerRanking(g)
2 >>> corr = g.computeOrdinalCorrelation(ko)
3 >>> g.showCorrelation(corr)
4 Correlation indexes:
5   Crisp ordinal correlation  : +0.483
6   Epistemic determination     :  0.230
7   Bipolar-valued equivalence : +0.111

```

But *Kohler's* ranking has a *dual* version, the prudent **Arrow-Raynaud ordering-by-choosing** rule, where a corresponding *max-min* strategy, when used on the *non-strict*

outranking digraph g , for ordering the from *last* to *first* produces a similar ranking result (see [LAM-2009], [DIA-2010]).

Noticing that the *NetFlows* score of an alternative x represents in fact a bipolar-valued characteristic of the assertion ‘**alternative x is ranked first**’, we may enhance *Kohler’s* or *Arrow-Raynaud’s* rules by replacing the *min-max*, respectively the *max-min*, strategy with an **iterated** maximal, respectively its *dual* minimal, *Netflows* score selection.

For a ranking (resp. an ordering) result, at step i (i goes from 1 to n) do the following:

1. Compute for each row of the bipolar-valued outranking relation table (see Listing 2.20) the corresponding *net flow score* (page 91) ;
2. Select the row where this score is maximal (resp. minimal); ties being resolved by lexicographic order;
3. Put the corresponding decision alternative at rank (resp. order) i ;
4. Delete the corresponding row and column from the relation table and restart until the table is empty.

A first *advantage* is that the so modified *Kohler’s* and *Arrow-Raynaud’s* rules become **invariant** under the *codual* transform. And we may get both the *ranking-by-choosing* as well as the *ordering-by-choosing* results with the `IteratedNetFlowsRanking` class constructor (see Listing 2.37 Lines 12-13).

Listing 2.37: Ordering-by-choosing with iterated minimal
NetFlows scores

```

1  >>> from linearOrders import IteratedNetFlowsRanking
2  >>> inf = IteratedNetFlowsRanking(g)
3  >>> inf
4  ----- Digraph instance description -----
5  Instance class      : IteratedNetFlowsRanking
6  Instance name       : rel_randomCBperftab_ranked
7  Digraph Order       : 9
8  Digraph Size        : 36
9  Valuation domain    : [-1.00;1.00]
10 Determinateness (%) : 100.00
11 Attributes          : ['valuedRanks', 'valuedOrdering',
12                           'iteratedNetFlowsRanking',
13                           'iteratedNetFlowsOrdering',
14                           'name', 'actions', 'order',
15                           'valuationdomain', 'relation',
16                           'gamma', 'notGamma']
17 >>> inf.iteratedNetFlowsOrdering
18  ['a2', 'a9', 'a1', 'a4', 'a3', 'a8', 'a7', 'a6', 'a5']
19 >>> corr = g.computeOrderCorrelation(inf.iteratedNetFlowsOrdering)
20 >>> g.showCorrelation(corr)
21 Correlation indexes:
22   Crisp ordinal correlation : +0.751

```

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```

23 Epistemic determination      :  0.230
24 Bipolar-valued equivalence : +0.173
25 >>> inf.iteratedNetFlowsRanking
26 ['a5', 'a7', 'a6', 'a3', 'a4', 'a1', 'a8', 'a9', 'a2']
27 >>> corr = g.computeRankingCorrelation(inf.iteratedNetFlowsRanking)
28 >>> g.showCorrelation(corr)
29 Correlation indexes:
30   Crisp ordinal correlation : +0.743
31   Epistemic determination    :  0.230
32   Bipolar-valued equivalence : +0.171

```

The iterated *NetFlows* ranking and its *dual*, the iterated *NetFlows* ordering, do not usually deliver both the same result (Listing 2.37 Lines 18 and 26). With our example outranking digraph g for instance, it is the *ordering-by-choosing* result that obtains a slightly better correlation with the given outranking digraph g (+0.751), a result that is also slightly better than *Kohler*'s original result (+0.747, see Listing 2.36 Line 8).

With different *ranking-by-choosing* and *ordering-by-choosing* results, it may be useful to *fuse* now, similar to what we have done before with *Kemeny*'s and *Slater's* optimal rankings (see Listing 2.32 and Listing 2.35), both, the iterated *NetFlows* ranking and ordering into a partial ranking. But we are hence back to the practical problem of what linear ranking should we eventually retain ?

Let us finally mention another interesting *ranking-by-choosing* approach.

Tideman's ranked-pairs rule

Tideman's ranking-by-choosing heuristic, the **RankedPairs** rule, working best this time on the non strict outranking digraph g , is based on a *prudent incremental* construction of linear orders that avoids on the fly any cycling outrankings (see [LAM-2009]). The ranking rule may be formulated as follows:

1. Rank the ordered pairs (x, y) of alternatives in decreasing order of $r(x \succsim y) + r(y \not\succsim x)$;
2. Consider the pairs in that order (ties are resolved by a lexicographic rule):
 - if the next pair does not create a *circuit* with the pairs already blocked, block this pair;
 - if the next pair creates a *circuit* with the already blocked pairs, skip it.

With our didactic outranking digraph g , we get the following result.

Listing 2.38: Computing a *RankedPairs* ranking

```

1 >>> from linearOrders import RankedPairsRanking
2 >>> rp = RankedPairsRanking(g)
3 >>> rp.showRanking()
4 ['a5', 'a6', 'a7', 'a3', 'a8', 'a9', 'a4', 'a1', 'a2']

```

The *RankedPairs* ranking rule renders in our example here luckily one of the two optimal *Kemeny* ranking, as we may verify below.

```

1 >>> ke.maximalRankings
2 [['a5', 'a6', 'a7', 'a3', 'a8', 'a9', 'a4', 'a1', 'a2'],
3  ['a5', 'a6', 'a7', 'a3', 'a9', 'a4', 'a1', 'a8', 'a2']]
4 >>> corr = g.computeOrdinalCorrelation(rp)
5 >>> g.showCorrelation(corr)
6 Correlation indexes:
7     Extended Kendall tau      : +0.779
8     Epistemic determination   :  0.230
9     Bipolar-valued equivalence : +0.179

```

Similar to *Kohler*'s rule, the *RankedPairs* rule has also a prudent *dual* version, the **Dias-Lamboray ordering-by-choosing** rule, which produces, when working this time on the co-dual *strict outranking* digraph *gcd*, a similar ranking result (see [LAM-2009], [DIA-2010]).

Besides of not providing a unique linear ranking, the *ranking-by-choosing* rules, as well as their dual *ordering-by-choosing* rules, are unfortunately *not scalable* to outranking digraphs of larger orders (> 100). For such bigger outranking digraphs, with several hundred or thousands of alternatives, only the *Copeland* and the *NetFlows* ranking-by-scoring rules, with a polynomial complexity of $O(n^2)$, where n is the order of the outranking digraph, remain in fact computationally tractable.

It is important finally to notice that for all outranking digraphs of small **or** larger orders there does usually **not exist** a unique optimal linear ranking result when the corresponding strict outranking digraph lacks transitivity and contains chordless cycles. In such a case, it may be interesting to compute a **ranking consensus** from multiple plausible linear rankings.

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2.5 On partially ranking outranking digraphs

- *Computing a ranking consensus from several linear rankings* (page 103)
- *On partially ranking with the Bachet rules* (page 106)
- *Consensus quality of the partial Bachet rankings* (page 109)

In this section, instead of computing linear rankings or orders, we illustrate two algorithmic strategies for computing *partial rankings* –partially determined transitive asymmetrical relations– from a given outranking digraph.

Computing a ranking consensus from several linear rankings

“... Competing criteria will yield different rankings of alternatives, with some shared elements and some divergent ones. The intersection –of the shared elements of the rankings – of the diverse orderings generated by the different priorities will yield a partial ordering that ranks some alternatives against each other with great clarity and internal consistency, while failing altogether to rank other pairs of alternatives.” – A. Sen, The Idea of Justice (2009)

To compare for instance the four rankings we have previously obtained with *ranking-by-scoring* strategies, it is worthwhile visualizing the **ranking consensus** one may observe between the *Copeland*, the *NetFlows* and both *Bachet* ranking results (see Listing 2.39 Lines 16-19). To compute such a ranking consensus we make usage of the *transitiveDigraphs.RankingsFusionDigraph* class (see Lines 20-21).

Listing 2.39: Computing a rankings consensus

```
1  >>> from outrankingDigraphs import *
2  >>> t = RandomCBPerformanceTableau(numberOfActions=9,
3  ...                               number_of_criteria=13, seed=200)
4  >>> g = BipolarOutrankingDigraph(t, Normalized=True)
5  >>> from linearOrders import *
6  >>> cop = CopelandOrder(g)
7  >>> ba = BachetRanking(g, Polarised=True, sampleSize=40)
8  >>> nf = NetFlowsRanking(g)
9  >>> bav = BachetRanking(g, Polarised=False, sampleSize=40,
10   ...                           Randomized=True, seed=11)
11 >>> rankings = [cop.copelandRanking,
12   ...                 ba.bachetRanking,
13   ...                 nf.netFlowsRanking,
14   ...                 bav.bachetRanking]
15 >>> rankings
16 [[['a5', 'a1', 'a6', 'a7', 'a8', 'a4', 'a9', 'a3', 'a2'],
17  ['a5', 'a6', 'a7', 'a3', 'a4', 'a1', 'a8', 'a9', 'a2'],
18  ['a5', 'a7', 'a6', 'a3', 'a1', 'a8', 'a4', 'a9', 'a2'],
19  ['a5', 'a6', 'a7', 'a3', 'a4', 'a8', 'a1', 'a2', 'a9']]]
20 >>> from transitiveDigraphs import RankingsFusionDigraph
21 >>> rfdg = RankingsFusionDigraph(g, rankings)
22 >>> rfdg
*----- Digraph instance description -----*
24 Instance class      : RankingsFusionDigraph
25 Instance name       : rel_randomCBperftab_wk
26 Digraph Order       : 9
27 Digraph Size        : 25
28 Valuation domain    : [-1.00;1.00]
29 Determinateness (%) : 84.72
30 Attributes          : ['name', 'actions', ... ,
31   ... 'valuationdomain', 'relation', ... ,
32   ... 'rankings', 'fusionoperator']
```

(continues on next page)

(continued from previous page)

```
33 >>> rfdg.isTransitive()
34 True
```

By *epistemic disjunctive fusion* (page 17) of the four *rankings*, the `RankingsFusionDigraph` constructor computes a transitive asymmetrical partial digraph (see Listing 2.39 Lines 33-34). Notice in Lines 16-19 the unstable ranks of alternative *a1* (rank 2,5,6 and 7) which induce contradictory ranking results leadind to many incomparability situations. Ranking and ordering of partial relations do not give now the same result when such incomparabilities do appear.

The generic `TransitiveDigraph` class provides therefore a `showTransitiveDigraph()` method which recursively extracts conjointly first and last choices –initial and terminal kernels– as shown in Listing 2.40 Lines 2-6 below.

Listing 2.40: Inspecting a partial ranking

```
1 >>> rfdg.showTransitiveDigraph()
2 Ranking by Choosing and Rejecting
3 1st ranked ['a5']
4     2nd ranked ['a1', 'a6', 'a7']
5     2nd last ranked ['a1', 'a3', 'a4', 'a8']
6     1st last ranked ['a2', 'a9']
```

The nine alternatives are gathered into four levels. Mind that alternative *a1* is at the same time 2nd-first and 2nd-last ranked (Lines 4-5). To draw such partial rankings, we make usage of an optimistic topological sort algorithm keeping ambiguously ranked alternatives on their best-ranked positions⁶⁰ (see Listing 2.41 Line 5).

⁶⁰ Topological Sort Algorithm 2.4 from *Algorithmic Graph Theory and Perfect Graphs* p.44 [GOL-2004].

Listing 2.41: Inspecting a partial ranking

```

1 >>> rfdg.exportGraphViz('rankingsByScoringFusion')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to rankingsByScoringFusion.dot
4 0 subgraph { rank = same; a5; }
5 1 subgraph { rank = same; a1; a6; a7; }
6 2 subgraph { rank = same; a3; a8; a4; }
7 3 subgraph { rank = same; a2; a9; }
8 dot -Grankdir=TB -Tpng rankingsByScoringFusion.dot \
9           -o rankingsByScoringFusion.png

```

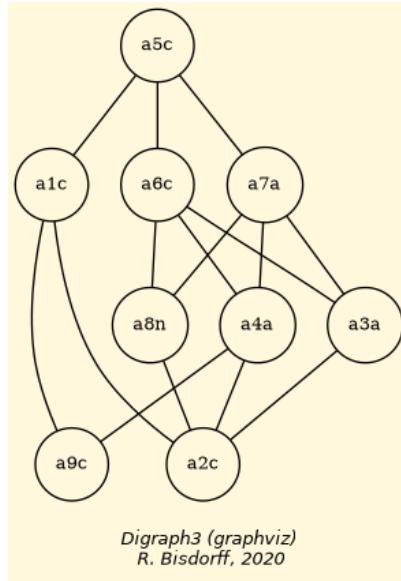


Fig. 2.18: *Copeland*, *NetFlows* and *Bachet* ranking consensus

Fig. 2.18 makes apparent a ranking consensus with the four levels of agreement where action a_5 appears consistently first-ranked and actions a_2 and a_9 , both, last-ranked. Notice the incomparabilities of alternatives a_1 and a_9 , a consequence of their contrasted performance records (see Fig. 2.15).

```

1 >>> g.showCorrelation(g.computeOrdinalCorrelation(rfdg))
2 Correlation indexes:
3   Crisp ordinal correlation : +0.847
4   Epistemic determination   : 0.157
5   Bipolar-valued equivalence : +0.133

```

The epistemic fusion of all four *ranking-by-scoring* results delivers here a convincing transitive partial ordering, highly correlated with the given outranking digraph g (+0.847), supported by a criteria significance majority of 56.6% (see Lines 3-5 above) .

A second strategy for constructing partial rankings makes usage of the *randomized Bachet* ranking rules.

On partially ranking with the *Bachet* rules

Due to its *Condorcet consistency* property, the polarised *Bachet* ranking rule applied to random orderings of the actions will potentially produce multiple ranking results of unequal correlation quality, yet respecting all the actual transitive part of the given outranking digraph. A subset of best correlated *Bachet* rankings represents hence a suitable sample for computing a convincing ranking consensus (see Bachet-Tutorial-label). This second strategy is provided by the `transitiveDigraphs.PartialBachetRanking` class. To illustrate its usefulness, let us reconsider the example outranking digraph g of Listing 2.39.

Listing 2.42: Partial polarised Bachet ranking digraph

```

1  >>> from outrankingDigraphs import *
2  >>> t = RandomCBPerformanceTableau(numberOfActions=9,
3  ...                               numberOfCriteria=13,seed=200)
4  >>> g = BipolarOutrankingDigraph(t,Normalized=True)
5  >>> from transitiveDigraphs import PartialBachetRanking
6  >>> pbr = PartialBachetRanking(g,Polarised=True,
7  ...                               randomized=100,seed=1,maxNbrOfRankings=5)
8  >>> pbr
9  *----- Digraph instance description -----*
10 Instance class      : PartialBachetRanking
11 Instance name       : rel_randomCBperftab_wk
12 Digraph Order       : 9
13 Digraph Size        : 27
14 Valuation domain    : [-1.00;1.00]
15 Determinateness (%) : 87.50
16 Attributes          : ['name', 'actions', 'order', ...,
17                           'valuationdomain', 'relation', ...,
18                           'randomized', 'seed', 'bachetRankings',
19                           'maxNbrOfRankings','Polarised',
20                           'partialBachetCorrelation']
21 >>> pbr.bachetRankings
22 [(0.6824, ['a5', 'a6', 'a3', 'a4', 'a1', 'a7', 'a8', 'a9', 'a2']),
23  (0.6523, ['a5', 'a6', 'a4', 'a7', 'a1', 'a3', 'a9', 'a2', 'a8']),
24  (0.6482, ['a5', 'a6', 'a4', 'a1', 'a7', 'a3', 'a9', 'a2', 'a8']),
25  (0.6442, ['a5', 'a6', 'a4', 'a3', 'a1', 'a7', 'a9', 'a8', 'a2']),
26  (0.6382, ['a5', 'a6', 'a1', 'a7', 'a3', 'a4', 'a8', 'a2', 'a9'])]
```

In Listing 2.42 Line 6-8, we notice that we sample 100 polarised *Bachet* rankings and keep the five best correlated rankings for constructing the ranking consensus. In Lines 21-26, we may notice that alternative a_5 is always first-ranked and alternative a_6 second-ranked. Whereas alternatives a_2 , a_8 and a_9 make up the tail group. The `showTransitiveDigraph()` method confirms this partial ranking (see Listing 2.43 Lines 2-6 below and Fig. 2.19).

Listing 2.43: Partial polarised Bachet ranking result

```

1 >>> pbr.showTransitiveDigraph()
2 Ranking by Choosing and Rejecting
3   1st ranked ['a5']
4     2nd ranked ['a6']
5       2nd last ranked ['a1', 'a3', 'a4', 'a7'])
6         1st last ranked ['a2', 'a8', 'a9'])
7 >>> pbr.showCorrelation(pbr.partialBachetCorrelation)
8 Correlation indexes:
9   Crisp ordinal correlation : +0.806
10  Epistemic determination   : 0.179
11  Bipolar-valued equivalence : +0.144
12 >>> pbr.exportGraphViz('partialBachetpol')
13 *---- exporting a dot file for GraphViz tools -----*
14   Exporting to partialBachetpol.dot
15   dot -Grankdir=TB -Tpng partialBachetpol.dot -o partialBachetpol.png

```

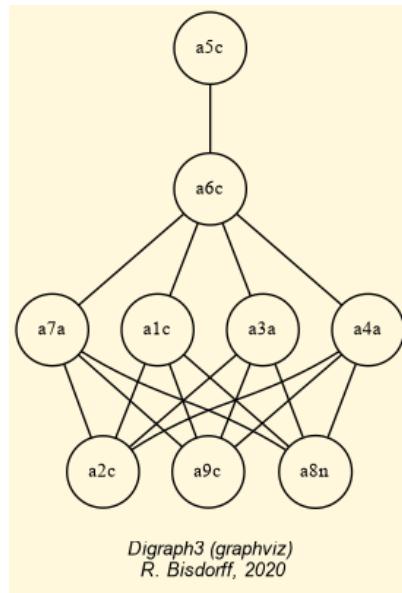


Fig. 2.19: Polarised Bachet partial ranking result

The resulting *partial ranking* is highly correlated with the common determinated part of the given outranking digraph g (+0.806) leading to a *relational equivalence* with the given outranking digraph g supported by a criteria significance majority of 57.2% (see Lines 9-11 above).

We recover with the polarised *Bachet* ranking rule a ranking consensus actually very similar to the previous consensus obtained from all four *ranking-by-scoring* results (see Fig. 2.18).

The `PartialBachetRanking` constructor uses by default the *polarised* version of the *Bachet* ranking rule. Due to its *Condorcet consistency* property, the partial ranking result obtained in Fig. 2.19 represents in fact a ranking consensus respecting the actual

transitive parts of the given outranking digraph (see the advanced topic dedicated to the Bachet ranking rules).

The `PartialBachetRanking` now provides a “**Polarised == False**” flag allowing to use instead the **valued** version of the *Bachet* ranking rule (see below Listing 2.44 Line 1). The five best qualified valued *Bachet* rankings are shown in Lines 4-8.

Listing 2.44: Five best correlated valued Bachet ranking results

```

1 >>> pvbr = PartialBachetRanking(g,Polarised=False,
2 ...           randomized=100,seed=1,maxNbrOfRankings=5)
3 >>> pvbr.bachetRankings
4 [(0.6764, ['a6', 'a5', 'a7', 'a4', 'a1', 'a8', 'a3', 'a2', 'a9']),
5 (0.6583, ['a5', 'a6', 'a7', 'a1', 'a3', 'a8', 'a2', 'a4', 'a9']),
6 (0.6543, ['a5', 'a6', 'a1', 'a7', 'a3', 'a8', 'a2', 'a4', 'a9']),
7 (0.6503, ['a5', 'a6', 'a7', 'a8', 'a3', 'a9', 'a2', 'a4', 'a1']),
8 (0.6462, ['a5', 'a6', 'a1', 'a7', 'a8', 'a2', 'a3', 'a4', 'a9'])]
```

Again we may notice that alternatives *a5* and *a6* are first-ranked and alternatives *a2*, *a4* and *a9* are last-ranked. It is worthwhile noticing in Lines 4-8 above that alternative *a1* appears in rank 3,4,5 and 9.

In Listing 2.45 Lines 3-6 we observe now a partial ranking taking into account not only the polarised relational structure, but also the **epistemic determination** of the given outranking digraph *g*. And the ordinal correlation with *g*, supported by a similar criteria significance of 57%, gets even higher: +0.888 vs +0.806 (see Lines 9-11).

Listing 2.45: Valued partial ranking result

```

1 >>> pvbr.showTransitiveDigraph()
2 Ranking by Choosing and Rejecting
3 1st ranked ['a5', 'a6']
4     2nd ranked ['a7'],
5     2nd last ranked ['a3', 'a8']
6     1st last ranked ['a1', 'a2', 'a4', 'a9']
7 >>> pvbr.showCorrelation(pvbr.partialBachetCorrelation)
8 Correlation indexes:
9     Crisp ordinal correlation : +0.888
10    Epistemic determination   :  0.157
11    Bipolar-valued equivalence: +0.139
12 >>> pvbr.exportGraphViz('partialBachetval')
13 *---- exporting a dot file for GraphViz tools -----
14 Exporting to partialBachetval.dot
15     dot -Grankdir=TB -Tpng partialBachetval.dot -o partialBachetval.png
```

It is worthwhile noticing in Fig. 2.20 that alternative *a1* appears indeed incomparable to the other alternatives except alternatives *a5* and *a6*, a fact already made previously apparent with the partial *polarised Bachet* ranking shown in Fig. 2.18.

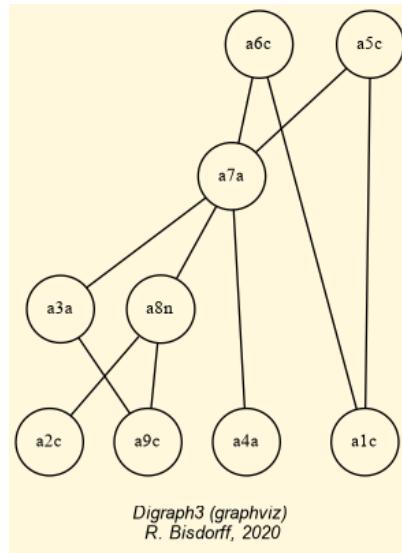


Fig. 2.20: Valued Bachet partial ranking result

Consensus quality of the partial Bachet rankings

Let us now verify in Listing 2.46 below the consensus quality of the partial polarised *Bachet* ranking *pbr*.

Listing 2.46: Consensus quality of the partial polarised Bachet ranking

```

1  >>> pbr.computePartialOutrankingConsensusQuality(Comments=True)
2  Consensus quality of partial polarised Bachet ranking
3  criterion (weight): bipolar-valued relational equivalence
4  -----
5  c01 (0.167): +0.444
6  b09 (0.050): +0.444
7  b02 (0.050): +0.358
8  b08 (0.050): +0.296
9  b04 (0.050): +0.259
10 b01 (0.050): +0.208
11 c02 (0.167): +0.074
12 b05 (0.050): +0.000
13 b10 (0.050): -0.095
14 b07 (0.050): -0.111
15 c03 (0.167): -0.148
16 b03 (0.050): -0.185
17 b06 (0.050): -0.245
18 Summary:
19   Weighted mean marginal correlation (a) : +0.108
20   Standard deviation (b)                 : +0.240
21   Partial ranking fairness (a)-(b)       : -0.132

```

Best correlated (+0.444) with the partial ranking appear *Cost* criterion *c01* and Benefit

criterion $b09$. The relational equivalences are supported by a nearly 75% significance majority (Lines 5-6). Eight out of thirteen criteria show a non negative equivalence and the weighted mean marginal equivalence is slightly positive (+0.108, Line 19). With a standard deviation of +0.240, we obtain however an overall negative fairness score of -0.132 for the partial polarised *Bachet* ranking.

We may redo in Listing 2.47 below the same computation for the partial valued *Bachet* ranking.

Listing 2.47: Consensus quality of the partial valued *Bachet* ranking

```

1 >>> pvbr.computePartialOutrankingConsensusQuality(Comments=True)
2 Consensus quality of the partial valued Bachet ranking
3 criterion (weight): bipolar-valued relational equivalence
4 -----
5 c01 (0.167): +0.472
6 b09 (0.050): +0.222
7 b05 (0.050): +0.194
8 b04 (0.050): +0.167
9 b01 (0.050): +0.139
10 b02 (0.050): +0.125
11 c02 (0.167): +0.083
12 b08 (0.050): +0.083
13 b07 (0.050): -0.056
14 b03 (0.050): -0.111
15 b10 (0.050): -0.111
16 c03 (0.167): -0.111
17 b06 (0.050): -0.181
18 Summary:
19 Weighted mean marginal correlation (a): +0.098
20 Standard deviation (b) : +0.204
21 Partial ranking fairness (a)-(b) : -0.107

```

The valued partial *Bachet* ranking pays a more accurate attention to the marginal criteria significance weights: $10/60 = 0.167$ for the three Costs criteria and $3/60 = 0.050$ for the Benefit criteria. Criteria $c01$ and $c03$ for instance, with a significance of 0.167, are hence given more attention. The weighted mean marginal correlation appears slightly lower (+0.098 vs +0.108). The standard deviation being however lower (+0.204 vs +0.240), we obtain a slightly better overall fairness score (-0.107 vs -0.132, see Lines 19-21).

As shown above, *Bachet* ranking rules may effectively deliver new methods for constructing convincing partial rankings and, by the way, a tool for computing potential first or last choice recommendations. Actually the initial and terminal prekernels of such partial transitive digraphs. Mind however that the *Bachet* ranking rules can only handle small outranking digraphs (< 50). For larger (> 50) or big (> 1000) outranking digraphs it is opportune to turn to order statistics and compute **weak rankings** –rankings with ties– by sorting the multicriteria performance records into *relative* or *absolute* performance **quantile equivalence classes**.

This order statistics based **rating** approach is presented in the following tutorials.

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2.6 Rating into relative performance quantiles

- *Performance quantile sorting on a single criterion* (page 111)
- *Rating-by-sorting into relative multicriteria performance quantiles* (page 112)
- *Rating-by-ranking with relative quantile limits* (page 115)

We apply order statistics for sorting a set X of n potential decision actions, evaluated on m incommensurable performance criteria, into q quantile equivalence classes, based on pairwise outranking characteristics involving the quantile class limits observed on each criterion. Thus we may implement a weak ordering algorithm of complexity $O(nmq)$.

Performance quantile sorting on a single criterion

A single criterion sorting category K is a (usually) lower-closed interval $[m_k; M_k[$ on a real-valued performance measurement scale, with $m_k \leq M_k$. If x is a measured performance on this scale, we may distinguish three sorting situations.

1. $x < m_k$ and $(x < M_k)$: The performance x is lower than category K .
2. $x \geq m_k$ and $x < M_k$: The performance x belongs to category K .
3. $x > m_k$ and $x \geq M_k$: The performance x is higher than category K .

As the relation $<$ is the dual of \geq ($\not\geq$), it will be sufficient to check that $x \geq m_k$ as well as $x \not\geq M_k$ are true for x to be considered a member of category K .

Upper-closed categories (in a more mathematical integration style) may as well be considered. In this case it is sufficient to check that $m_k \not\geq x$ as well as $M_k \geq x$ are true for x to be considered a member of category K . It is worthwhile noticing that a category K such that $m_k = M_k$ is hence always empty by definition. In order to be able to properly sort over the complete range of values to be sorted, we will need to use a special, two-sided closed last, respectively first, category.

Let $K = K_1, \dots, K_q$ be a non trivial partition of the criterion's performance measurement scale into $q \geq 2$ ordered categories K_k – i.e. lower-closed intervals $[m_k; M_k[$ – such that $m_k < M_k$, $M_k = m_{k+1}$ for $k = 0, \dots, q - 1$ and $M_q = \infty$. And, let $A = \{a_1, a_2, a_3, \dots\}$ be a finite set of not all equal performance measures observed on the scale in question.

Property: For all performance measure $x \in A$ there exists now a unique k such that $x \in K_k$. If we assimilate, like in descriptive statistics, all the measures gathered in a category K_k to the central value of the category – i.e. $(m_k + M_k)/2$ – the sorting result will hence define a weak order (complete preorder) on A .

Let $Q = \{Q_0, Q_1, \dots, Q_q\}$ denote the set of $q + 1$ increasing order-statistical quantiles –like quartiles or deciles– we may compute from the ordered set A of performance measures

observed on a performance scale. If $Q_0 = \min(X)$, we may, with the following intervals: $[Q_0; Q_1[, [Q_1; Q_2[, \dots, [Q_{q-1}; \infty[$, hence define a set of q lower-closed sorting categories. And, in the case of upper-closed categories, if $Q_q = \max(X)$, we would obtain the intervals $] - \infty; Q_1],]Q_1; Q_2], \dots,]Q_{q-1}; Q_q]$. The corresponding sorting of A will result, in both cases, in a repartition of all measures x into the q quantile categories K_k for $k = 1, \dots, q$.

Example: Let $A = \{a_7 = 7.03, a_{15} = 9.45, a_{11} = 20.35, a_{16} = 25.94, a_{10} = 31.44, a_9 = 34.48, a_{12} = 34.50, a_{13} = 35.61, a_{14} = 36.54, a_{19} = 42.83, a_5 = 50.04, a_2 = 59.85, a_{17} = 61.35, a_{18} = 61.61, a_3 = 76.91, a_6 = 91.39, a_1 = 91.79, a_4 = 96.52, a_8 = 96.56, a_{20} = 98.42\}$ be a set of 20 increasing performance measures observed on a given criterion. The lower-closed category limits we obtain with quartiles ($q = 4$) are: $Q_0 = 7.03 = a_7, Q_1 = 34.485, Q_2 = 54.945$ (median performance), and $Q_3 = 91.69$. And the sorting into these four categories defines on A a complete preorder with the following four equivalence classes: $K_1 = \{a_7, a_{10}, a_{11}, a_{10}, a_{15}, a_{16}\}$, $K_2 = \{a_5, a_9, a_{13}, a_{14}, a_{19}\}$, $K_3 = \{a_2, a_3, a_6, a_{17}, a_{18}\}$, and $K_4 = \{a_1, a_4, a_8, a_{20}\}$.

Rating-by-sorting into relative multicriteria performance quantiles

Let us now suppose that we are given a performance tableau with a set X of n decision alternatives evaluated on a coherent family of m performance criteria associated with the corresponding outranking relation \succsim defined on X . We denote x_j the performance of alternative x observed on criterion j .

Suppose furthermore that we want to sort the decision alternatives into q upper-closed quantile equivalence classes. We therefore consider a series : $k = k/q$ for $k = 0, \dots, q$ of $q+1$ equally spaced quantiles, like quartiles: 0, 0.25, 0.5, 0.75, 1; quintiles: 0, 0.2, 0.4, 0.6, 0.8, 1; or deciles: 0, 0.1, 0.2, ..., 0.9, 1, for instance.

The upper-closed \mathbf{q}^k class corresponds to the m quantile intervals $]q_j(p_{k-1}); q_j(p_k)]$ observed on each criterion j , where $k = 2, \dots, q$, $q_j(p_0) = \max_X(x_j)$, and the first class gathers all performances below or equal to $Q_j(p_1)$.

The lower-closed \mathbf{q}_k class corresponds to the m quantile intervals $[q_j(p_{k-1}); q_j(p_k)]$ observed on each criterion j , where $k = 1, \dots, q-1$, $q_j(p_0) = \min_X(x_j)$, and the last class gathers all performances above or equal to $Q_j(p_{q-1})$.

We call **q-tiles** a complete series of $k = 1, \dots, q$ upper-closed \mathbf{q}^k , respectively lower-closed \mathbf{q}_k , multiple criteria quantile classes.

Property: With the help of the bipolar-valued characteristic of the outranking relation $r(\succsim)$ we may compute the bipolar-valued characteristic of the assertion: x belongs to upper-closed q -tiles class \mathbf{q}^k class, resp. lower-closed class \mathbf{q}_k , as follows.

$$\begin{aligned} r(x \in \mathbf{q}^k) &= \min [-r(\mathbf{q}(p_{q-1}) \succsim x), r(\mathbf{q}(p_q) \succsim x)] \\ r(x \in \mathbf{q}_k) &= \min [r(x \succsim \mathbf{q}(p_{q-1}), -r(x \succsim \mathbf{q}(p_q)] \end{aligned}$$

The outranking relation \succsim verifying the coduality principle, $-r(\mathbf{q}(p_{q-1}) \succsim x) = r(\mathbf{q}(p_{q-1}) \prec x)$, resp. $-r(x \succsim \mathbf{q}(p_q)) = r(x \prec \mathbf{q}(p_q))$.

We may compute, for instance, a five-tiling of a given random performance tableau with the help of the `ratingDigraphs.RatingByRelativeQuantilesDigraph` class.

Listing 2.48: Computing a quintiles rating result

```

1  >>> from randomPerfTabs import RandomPerformanceTableau
2  >>> t = RandomPerformanceTableau(numberOfActions=50, seed=5)
3  >>> from ratingDigraphs import RatingByRelativeQuantilesDigraph
4  >>> rqr = RatingByRelativeQuantilesDigraph(t, quantiles=5)
5  >>> rqr
6      ----- Object instance description -----
7      Instance class      : RatingByRelativeQuantilesDigraph
8      Instance name       : relative_rating_randomperftab
9      Actions             : 55
10     Criteria            : 7
11     Quantiles           : 5
12     Lowerclosed         : False
13     Rankingrule         : NetFlows
14     Size                : 1647
15     Valuation domain    : [-1.00;1.00]
16     Determinateness (%) : 67.40
17     Attributes          : ['name', 'actions', 'actionsOrig',
18                           'criteria', 'evaluation', 'NA', 'runTimes',
19                           'quantilesFrequencies', 'LowerClosed', 'categories',
20                           'criteriaCategoryLimits', 'limitingQuantiles', 'profiles',
21                           'profileLimits', 'order', 'nbrThreads', 'relation',
22                           'valuationdomain', 'sorting', 'relativeCategoryContent',
23                           'sortingRelation', 'rankingRule', 'rankingScores',
24                           'rankingCorrelation', 'actionsRanking', 'ratingCategories']
25     ----- Constructor run times (in sec.) -----
26     Threads             : 1
27     Total time          : 0.19248
28     Data input          : 0.00710
29     Compute quantiles   : 0.00117
30     Compute outrankings : 0.17415
31     rating-by-sorting  : 0.00074
32     rating-by-ranking   : 0.00932
33 >>> rqr.showSorting()
34     ---- Sorting results in descending order ---*
35     ]0.80 - 1.00]: ['a22']
36     ]0.60 - 0.80]: ['a03', 'a07', 'a08', 'a11', 'a14', 'a17',
37                           'a19', 'a20', 'a29', 'a32', 'a33', 'a37',
38                           'a39', 'a41', 'a42', 'a49']
39     ]0.40 - 0.60]: ['a01', 'a02', 'a04', 'a05', 'a06', 'a08',
40                           'a09', 'a16', 'a17', 'a18', 'a19', 'a21',
41                           'a24', 'a27', 'a28', 'a30', 'a31', 'a35',
42                           'a36', 'a40', 'a43', 'a46', 'a47', 'a48',
43                           'a49', 'a50']
44     ]0.20 - 0.40]: ['a04', 'a10', 'a12', 'a13', 'a15', 'a23',
45                           'a25', 'a26', 'a34', 'a38', 'a43', 'a44'],

```

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```
46          'a45', 'a49']
47 ] < - 0.20]: ['a44']
```

Most of the decision actions (26) are gathered in the median quintile $]0.40 - 0.60]$ class, whereas the highest quintile $]0.80 - 1.00]$ and the lowest quintile $] < -0.20]$ classes gather each one a unique decision alternative ($a22$, resp. $a44$) (see Listing 2.48 Lines XX-).

We may inspect as follows the details of the corresponding sorting characteristics.

Listing 2.49: Bipolar-valued sorting characteristics (extract)

```
1  >>> rqr.valuationdomain
2  {'min': Decimal('-1.0'), 'med': Decimal('0'),
3   'max': Decimal('1.0')}
4  >>> rqr.showSortingCharacteristics()
5    x in q^k      r(q^k-1 < x)  r(q^k >= x)  r(x in q^k)
6  a22 in ]< - 0.20]  1.00      -0.86      -0.86
7  a22 in ]0.20 - 0.40]  0.86      -0.71      -0.71
8  a22 in ]0.40 - 0.60]  0.71      -0.71      -0.71
9  a22 in ]0.60 - 0.80]  0.71      -0.14      -0.14
10 a22 in ]0.80 - 1.00]  0.14      1.00      0.14
11 ...
12 ...
13 a44 in ]< - 0.20]  1.00      0.00      0.00
14 a44 in ]0.20 - 0.40]  0.00      0.57      0.00
15 a44 in ]0.40 - 0.60]  -0.57     0.86      -0.57
16 a44 in ]0.60 - 0.80]  -0.86     0.86      -0.86
17 a44 in ]0.80 - 1.00]  -0.86     0.86      -0.86
18 ...
19 ...
20 a49 in ]< - 0.20]  1.00      -0.43     -0.43
21 a49 in ]0.20 - 0.40]  0.43      0.00      0.00
22 a49 in ]0.40 - 0.60]  0.00      0.00      0.00
23 a49 in ]0.60 - 0.80]  0.00      0.57      0.00
24 a49 in ]0.80 - 1.00]  -0.57     0.86      -0.57
```

Alternative $a22$ verifies indeed positively both sorting conditions only for the highest quintile $[0.80 - 1.00]$ class (see Listing 2.49 Lines 10). Whereas alternatives $a44$ and $a49$, for instance, weakly verify both sorting conditions each one for two, resp. three, adjacent quintile classes (see Lines 13-14 and 21-23).

Quantiles sorting results indeed always verify the following **Properties**.

1. **Coherence:** Each object is sorted into a non-empty subset of *adjacent* q-tiles classes. An alternative that would *miss* evaluations on all the criteria will be sorted conjointly in all q-tiled classes.
2. **Uniqueness:** If $r(x \in \mathbf{q}^k) \neq 0$ for $k = 1, \dots, q$, then performance x is sorted into

exactly one single q-tiled class.

3. **Separability:** Computing the sorting result for performance x is independent from the computing of the other performances' sorting results. This property gives access to efficient parallel processing of class membership characteristics.

The q -*tiles* sorting result leaves us hence with more or less *overlapping* ordered quantile equivalence classes. For constructing now a linearly ranked q -tiles partition of X , we may apply three strategies:

1. **Average** (default): In decreasing lexicographic order of the average of the lower and upper quantile limits and the upper quantile class limit;
2. **Optimistic:** In decreasing lexicographic order of the upper and lower quantile class limits;
3. **Pessimistic:** In decreasing lexicographic order of the lower and upper quantile class limits;

Listing 2.50: Weakly ranking the quintiles sorting result

```

1 >>> rqr.showRatingByQuantilesSorting(strategy='average')
2 [0.80-1.00] : ['a22']
3 ]0.60-0.80] : ['a03', 'a07', 'a11', 'a14', 'a20', 'a29',
4           'a32', 'a33', 'a37', 'a39', 'a41', 'a42']
5 ]0.40-0.80] : ['a08', 'a17', 'a19']
6 ]0.20-0.80] : ['a49']
7 ]0.40-0.60] : ['a01', 'a02', 'a05', 'a06', 'a09', 'a16',
8           'a18', 'a21', 'a24', 'a27', 'a28', 'a30',
9           'a31', 'a35', 'a36', 'a40', 'a46', 'a47',
10          'a48', 'a50']
11 ]0.20-0.60] : ['a04', 'a43']
12 ]0.20-0.40] : ['a10', 'a12', 'a13', 'a15', 'a23', 'a25',
13           'a26', 'a34', 'a38', 'a45']
14 ] < -0.40] : ['a44']

```

Following, for instance, the *average* ranking strategy, we find confirmed in the weak ranking shown in Listing 2.50, that alternative $a49$ is indeed sorted into three adjacent quintiles classes, namely $]0.20 - 0.80]$ (see Line 6) and precedes the $]0.40 - 0.60]$ class, of same average of lower and upper limits.

Rating-by-ranking with relative quantile limits

The *actions* attribute of a `RatingByRelativeQuantilesDigraph` class instance contains, besides the *decision actions* gathered from the given performance tableau (stored in the *actionsOrig* attribute, also the quantile limits observed on all the criteria (stored in the *limitingquantiles* attribute, see Listing 2.48 Line 20).

Listing 2.51: The quintiling of the performance evaluation data per criterion

```

1 >>> rqr.showCriteriaQuantileLimits()
2 Quantile Class Limits (q = 5)
3 Upper-closed classes
4 crit.      0.20    0.40    0.60    0.80    1.00
5 -----
6 g1        31.35   41.09   58.53   71.91   98.08
7 g2        27.81   39.19   49.87   61.66   96.18
8 g3        25.10   34.78   49.45   63.97   92.59
9 g4        24.61   37.91   53.91   71.02   89.84
10 g5       26.94   36.43   52.16   72.52   96.25
11 g6       23.94   44.06   54.92   67.34   95.97
12 g7       30.94   47.40   55.46   69.04   97.10

```

We may hence rank this extended actions attribute as follows with the *NetFlows* ranking rule –default with the *RatingByRelativeQuantilesDigraph* class.

Listing 2.52: Rating by ranking the quintiling of the performance tableau

```

1 >>> rqr.computeNetFlowsRanking()
2 ['5-M', '4-M', 'a22', 'a42', 'a07', 'a33', 'a03', 'a01',
3  'a39', 'a48', 'a37', 'a29', 'a41', 'a11', 'a27', 'a05',
4  'a46', 'a02', 'a17', 'a32', '3-M', 'a14', 'a12', 'a20',
5  'a13', 'a08', 'a06', 'a24', 'a47', 'a31', 'a09', 'a21',
6  'a19', 'a43', 'a49', 'a50', 'a40', 'a28', 'a38', 'a25',
7  'a45', 'a18', 'a16', 'a36', 'a35', 'a30', 'a23', 'a34',
8  'a15', '2-M', 'a10', 'a26', 'a04', 'a44', '1-M']
9 >>> rqr.showRatingByQuantilesRanking()
10 ----- rating by quantiles ranking result -----
11 ]0.60 - 0.80] ['a22', 'a42', 'a07', 'a33', 'a03', 'a01',
12          'a39', 'a48', 'a37', 'a29', 'a41', 'a11',
13          'a27', 'a05', 'a46', 'a02', 'a17', 'a32']
14 ]0.40 - 0.60] ['a14', 'a12', 'a20', 'a13', 'a08', 'a06',
15          'a24', 'a47', 'a31', 'a09', 'a21', 'a19',
16          'a43', 'a49', 'a50', 'a40', 'a28', 'a38',
17          'a25', 'a45', 'a18', 'a16', 'a36', 'a35',
18          'a30', 'a23', 'a34', 'a15']
19 ]0.20 - 0.40] ['a10', 'a26', 'a04', 'a44']

```

As we are rating into upperclosed quintiles, we obtain from the ranking above an immediate precise rating result. No performance record is rated in the lowest quintile $[0.00 - 0.20]$ and in the highest quintile $[0.80 - 1.00]$ and 28 out of the 50 records are rated in the midfiled, i.e. the median quintile $[0.40 - 0.60]$.

The rating-by-ranking delivers thus a precise quantiling of a given performance tableau. One must however not forget that there does not exist a single optimal ranking rule, and

various ranking heuristics may render also various more or less diverging rating results.

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2.7 Rating with learned performance quantile norms

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- [Incremental learning of historical performance quantiles](#) (page 118)
- [Rating-by-ranking new performances with quantile norms](#) (page 120)

Introduction

In this tutorial we address the problem of **rating multiple criteria performances** of a set of potential decision alternatives with respect to empirical order statistics, i.e. performance quantiles learned from historical performance data gathered from similar decision alternatives observed in the past (see [CPSTAT-L5]).

To illustrate the decision problem we face, consider for a moment that, in a given decision aid study, we observe, for instance in the Table below, the multi-criteria performances of two potential decision alternatives, named *a1001* and *a1010*, marked on **7 incommensurable** preference criteria: 2 **costs** criteria *c1* and *c2* (to **minimize**) and 5 **benefits** criteria *b1* to *b5* (to **maximize**).

Criterion	b1	b2	b3	b4	b5	c1	c2
weight	2	2	2	2	2	5	5
<i>a1001</i>	37.0	2	2	61.0	31.0	-4	-40.0
<i>a1010</i>	32.0	9	6	55.0	51.0	-4	-35.0

The performances on *benefits* criteria *b1*, *b4* and *b5* are measured on a cardinal scale from 0.0 (worst) to 100.0 (best) whereas, the performances on the *benefits* criteria *b2* and *b3* and on the *cost* criterion *c1* are measured on an ordinal scale from 0 (worst) to 10 (best), respectively -10 (worst) to 0 (best). The performances on the *cost* criterion *c2* are again measured on a cardinal negative scale from -100.00 (worst) to 0.0 (best).

The importance (sum of weights) of the *costs* criteria is **equal** to the importance (sum of weights) of the *benefits* criteria taken all together.

The non trivial decision problem we now face here, is to decide, how the multiple criteria performances of *a1001*, respectively *a1010*, may be rated (**excellent** ? **good** ?, or **fair** ?; perhaps even, **weak** ? or **very weak** ?) in an **order statistical sense**, when compared with all potential similar multi-criteria performances one has already encountered in the past.

To solve this *absolute* rating decision problem, first, we need to estimate multi-criteria **performance quantiles** from historical records.

Incremental learning of historical performance quantiles

Suppose that we see flying in random multiple criteria performances from a given model of random performance tableau (see the `randomPerfTabs` module). The question we address here is to estimate empirical performance quantiles on the basis of so far observed performance vectors. For this task, we are inspired by [CHAM-2006] and [NR3-2007], who present an efficient algorithm for incrementally updating a quantile-binned cumulative distribution function (CDF) with newly observed CDFs.

The `PerformanceQuantiles` class implements such a performance quantiles estimation based on a given performance tableau. Its main components are:

- Ordered **objectives** and a **criteria** dictionaries from a valid performance tableau instance;
- A list **quantileFrequencies** of quantile frequencies like *quartiles* [0.0, 0.25, 05, 0.75, 1.0], *quintiles* [0.0, 0.2, 0.4, 0.6, 0.8, 1.0] or *deciles* [0.0, 0.1, 0.2, ..., 1.0] for instance;
- An ordered dictionary **limitingQuantiles** of so far estimated *lower* (default) or *upper* quantile class limits for each frequency per criterion;
- An ordered dictionary **historySizes** for keeping track of the number of evaluations seen so far per criterion. Missing data may make these sizes vary from criterion to criterion.

Below, an example Python session concerning 900 decision alternatives randomly generated from a *Cost-Benefit* Performance tableau model from which are also drawn the performances of alternatives *a1001* and *a1010* above.

Listing 2.53: Computing performance quantiles from a given performance tableau

```
1  >>> from performanceQuantiles import PerformanceQuantiles
2  >>> from randomPerfTabs import RandomCBPerformanceTableau
3  >>> nbrActions=900
4  >>> nbrCrit = 7
5  >>> seed = 100
6  >>> tp = RandomCBPerformanceTableau(numberOfActions=nbrActions,
7  ...                               numberOfCriteria=nbrCrit,seed=seed)
8
9  >>> pq = PerformanceQuantiles(tp,
10 ...                               numberOfBins = 'quartiles',
11 ...                               LowerClosed=True)
12
13 >>> pq
14 *----- PerformanceQuantiles instance description -----*
15 Instance class      : PerformanceQuantiles
16 Instance name       : 4-tiled_performances
17 # Objectives        : 2
18 # Criteria          : 7
```

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```

19 # Quantiles      : 4
20 # History sizes : {'c1': 887, 'b1': 888, 'b2': 891, 'b3': 895,
21             'b4': 892, 'c2': 893, 'b5': 887}
22 Attributes      : ['perfTabType', 'valueDigits', 'actionsTypeStatistics
23             ↴',
24             'objectives', 'BigData', 'missingDataProbability',
25             'criteria', 'LowerClosed', 'name',
26             'quantilesFrequencies', 'historySizes',
             'limitingQuantiles', 'cdf']

```

The `PerformanceQuantiles` class parameter `numberOfBins` (see Listing 2.53 Line 10 above), choosing the wished number of quantile frequencies, may be either **quartiles** (4 bins), **quintiles** (5 bins), **deciles** (10 bins), **dodeciles** (20 bins) or any other integer number of quantile bins. The quantile bins may be either **lower closed** (default) or **upper-closed**.

Listing 2.54: Printing out the estimated quartile limits

```

1 >>> pq.showLimitingQuantiles(ByObjectives=True)
2 ---- Historical performance quantiles ----*
3 Costs
4 criteria | weights | '0.00'   '0.25'   '0.50'   '0.75'   '1.00'
5 -----|-----|-----|-----|-----|-----|-----|
6   'c1'  |    5    |   -10     -7     -5     -3      0
7   'c2'  |    5    | -96.37   -70.65   -50.10   -30.00  -1.43
8 Benefits
9 criteria | weights | '0.00'   '0.25'   '0.50'   '0.75'   '1.00'
10 -----|-----|-----|-----|-----|-----|-----|
11   'b1'  |    2    |   1.99    29.82   49.44    70.73   99.83
12   'b2'  |    2    |     0      3       5       7      10
13   'b3'  |    2    |     0      3       5       7      10
14   'b4'  |    2    |   3.27    30.10   50.82    70.89   98.05
15   'b5'  |    2    |   0.85    29.08   48.55    69.98   97.56

```

Both objectives are **equi-important**; the sum of weights (10) of the *costs* criteria balance the sum of weights (10) of the *benefits* criteria (see Listing 2.54 column 2). The preference direction of the *costs* criteria *c1* and *c2* is **negative**; the lesser the costs the better it is, whereas all the *benefits* criteria *b1* to *b5* show **positive** preference directions, i.e. the higher the benefits the better it is. The columns entitled ‘0.00’, resp. ‘1.00’ show the *quartile Q0*, resp. *Q4*, i.e. the **worst**, resp. **best** performance observed so far on each criterion. Column ‘0.50’ shows the **median** (*Q2*) performance observed on the criteria.

New decision alternatives with random multiple criteria performance vectors from the same random performance tableau model may now be generated with ad hoc random performance generators. We provide for experimental purpose, in the `randomPerfTabs` module, three such generators: one for the standard `RandomPerformanceTableau` model, one for the two objectives `RandomCBPerformanceTableau` Cost-Benefit model, and one for the `Random3ObjectivesPerformanceTableau` model with three objectives con-

cerning respectively economic, environmental or social aspects.

Given a new Performance Tableau with 100 new decision alternatives, the so far estimated historical quantile limits may be updated as follows:

Listing 2.55: Generating 100 new random decision alternatives of the same model

```

1 >>> from randomPerfTabs import RandomPerformanceGenerator
2 >>> rpg = RandomPerformanceGenerator(tp, seed=seed)
3 >>> newTab = rpg.randomPerformanceTableau(100)
4 >>> # Updating the quartile norms shown above
5 >>> pq.updateQuantiles(newTab, historySize=None)
```

Parameter *historySize* (see Listing 2.55 Line 5) of the `updateQuantiles()` method allows to **balance** the **new** evaluations against the **historical** ones. With `historySize = None` (the default setting), the balance in the example above is 900/1000 (90%, weight of historical data) against 100/1000 (10%, weight of the new incoming observations). Putting `historySize = 0`, for instance, will ignore all historical data (0/100 against 100/100) and restart building the quantile estimation with solely the new incoming data. The updated quantile limits may be shown in a browser view (see Fig. 2.21).

```

1 >>> # showing the updated quartile limits in a browser view
2 >>> pq.showHTMLLimitingQuantiles(Transposed=True)
```

Performance quantiles

Sampling sizes between 986 and 995.

criterion	0.00	0.25	0.50	0.75	1.00
b1	1.99	28.77	49.63	75.27	99.83
b2	0.00	2.94	4.92	6.72	10.00
b3	0.00	2.90	4.86	8.01	10.00
b4	3.27	35.91	58.58	72.00	98.05
b5	0.85	32.84	48.09	69.75	99.00
c1	-10.00	-7.35	-5.39	-3.38	0.00
c2	-96.37	-72.22	-52.27	-33.99	-1.43

Fig. 2.21: Showing the updated quartile limits

Rating-by-ranking new performances with quantile norms

For **absolute rating** of a newly given set of decision alternatives with the help of empirical performance quantiles estimated from historical data, we provide the `RatingByLearnedQuantilesDigraph` class from the `ratingDigraphs` module. The rat-

ing result is computed by **ranking** the new performance records together with the learned quantile limits. The constructor requires a valid **PerformanceQuantiles** instance.

Note

It is important to notice that the **RatingByLearnedQuantilesDigraph** class, contrary to the generic **OutrankingDigraph** class, does not only inherit from the generic **PerformanceTableau** class, but also from the **PerformanceQuantiles** class. The **actions** in such a **RatingByLearnedQuantilesDigraph** instance do not contain only the newly given decision alternatives, but also the historical quantile profiles obtained from a given **PerformanceQuantiles** instance, i.e. estimated quantile bins' performance limits from historical performance data.

We reconsider the **PerformanceQuantiles** object instance *pq* as computed in the previous section. Let *newActions* be a list of 10 new decision alternatives generated with the same random performance tableau model and including the two decision alternatives *a1001* and *a1010* mentioned at the beginning.

Listing 2.56: Computing an absolute rating of 10 new decision alternatives

```

1  >>> from ratingDigraphs import\
2      RatingByLearnedQuantilesDigraph
3  >>> newActions = rpg.randomActions(10)
4  >>> lqr = RatingByLearnedQuantilesDigraph(pq,newActions,
5      rankingRule='best')
6  >>> lqr
7  *----- Object instance description -----*
8  Instance class      : RatingByLearnedQuantilesDigraph
9  Instance name       : learnedRatingDigraph
10 Actions             : 14
11 Criteria            : 7
12 Quantiles           : 4
13 Lowerclosed         : True
14 Rankingrule         : Copeland
15 Size                : 93
16 Valuation domain   : [-1.00;1.00]
17 Determinateness (%): 76.09
18 Attributes          : ['runTimes', 'objectives', 'criteria',
19     'LowerClosed', 'quantilesFrequencies', 'criteriaCategoryLimits',
20     'limitingQuantiles', 'historySizes', 'cdf', 'NA', 'name',
21     'newActions', 'evaluation', 'actionsOrig', 'actions',
22     'categories', 'profiles', 'profileLimits', 'order',
23     'nbrThreads', 'relation', 'valuationdomain', 'sorting',
24     'relativeCategoryContent', 'sortingRelation', 'rankingRule',
25     'rankingCorrelation', 'rankingScores', 'actionsRanking',
26     'ratingCategories']
```

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```

27      *----- Constructor run times (in sec.) -----*
28      Threads          : 1
29      Total time       : 0.03680
30      Data input        : 0.00119
31      Compute quantiles : 0.00014
32      Compute outrankings : 0.02771
33      rating-by-sorting : 0.00033
34      rating-by-ranking : 0.00742

```

Data input to the `RatingByLearnedQuantilesDigraph` class constructor (see Listing 2.56 Line 4) are a valid `PerformanceQuantiles` object `pq` and a compatible list `newActions` of new decision alternatives generated from the same random origin.

Let us have a look at the digraph's nodes, here called **newActions**.

Listing 2.57: Performance tableau of the new incoming decision alternatives

```

1 >>> lqr.showPerformanceTableau(actionsSubset=lqr.newActions)
2      *----- performance tableau -----*
3      criteria | a1001 a1002 a1003 a1004 a1005 a1006 a1007 a1008 a1009 a1010
4      -----|-----
5      'b1'   |  37.0  27.0  24.0  16.0  42.0  33.0  39.0  64.0  42.0  32.0
6      'b2'   |   2.0   5.0   8.0   3.0   3.0   3.0   6.0   5.0   4.0   9.0
7      'b3'   |   2.0   4.0   2.0   1.0   6.0   3.0   2.0   6.0   6.0   6.0
8      'b4'   |  61.0  54.0  74.0  25.0  28.0  20.0  20.0  49.0  44.0  55.0
9      'b5'   |  31.0  63.0  61.0  48.0  30.0  39.0  16.0  96.0  57.0  51.0
10     'c1'   |  -4.0  -6.0  -8.0  -5.0  -1.0  -5.0  -1.0  -6.0  -6.0  -4.0
11     'c2'   | -40.0 -23.0 -37.0 -37.0 -24.0 -27.0 -73.0 -43.0 -94.0 -35.0

```

Among the 10 new incoming decision alternatives (see Listing 2.57), we recognize alternatives `a1001` (see column 2) and `a1010` (see last column) we have mentioned in our introduction.

The `RatingByLearnedQuantilesDigraph` class instance's `actions` dictionary includes as well the closed lower limits of the four quartile classes: $m1 = [0.0 -]$, $m2 = [0.25 -]$, $m3 = [0.5 -]$, $m4 = [0.75 -]$. We find these limits in a `profiles` attribute (see Listing 2.58 below).

Listing 2.58: Showing the limiting profiles of the rating quantiles

```

1 >>> lqr.showPerformanceTableau(actionsSubset=lqr.profiles)
2      *----- Quartiles limit profiles -----*
3      criteria | 'm1'    'm2'    'm3'    'm4'
4      -----|-----
5      'b1'   |  2.0    28.8   49.6   75.3
6      'b2'   |  0.0    2.9    4.9    6.7

```

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7	'b3'		0.0	2.9	4.9	8.0
8	'b4'		3.3	35.9	58.6	72.0
9	'b5'		0.8	32.8	48.1	69.7
10	'c1'		-10.0	-7.4	-5.4	-3.4
11	'c2'		-96.4	-72.2	-52.3	-34.0

The main run time (see Listing 2.56 Lines 27-) is spent by the class constructor in computing a bipolar-valued outranking relation on the extended actions set including both the new alternatives as well as the quartile class limits. In case of large volumes, i.e. many new decision alternatives and centile classes for instance, a multi-threading version may be used when multiple processing cores are available (see the technical description of the `RatingByLearnedQuantilesDigraph` class).

The actual rating procedure will rely on a complete ranking of the new decision alternatives as well as the quantile class limits obtained from the corresponding bipolar-valued outranking digraph. Two efficient and scalable ranking rules, the **Copeland** and its valued version, the **Netflows** rule may be used for this purpose. The `rankingRule` parameter allows to choose one of both. With `rankingRule='best'` (see Listing 2.58 Line 4) the `RatingByLearnedQuantilesDigraph` constructor will choose the ranking rule that results in the highest ordinal correlation with the given outranking relation (see [BIS-2012]).

In this rating example, the *Copeland* rule appears to be the more appropriate ranking rule.

Listing 2.59: Copeland ranking of new alternatives and historical quartile limits

```

1 >>> lqr.rankingRule
2   'Copeland'
3 >>> lqr.actionsRanking
4   ['m4', 'a1005', 'a1010', 'a1002', 'a1008', 'a1006', 'a1001',
5    'a1003', 'm3', 'a1007', 'a1004', 'a1009', 'm2', 'm1']
6 >>> lqr.showCorrelation(lqr.rankingCorrelation)
7 Correlation indexes:
8   Crisp ordinal correlation : +0.945
9   Epistemic determination   :  0.522
10  Bipolar-valued equivalence : +0.493

```

We achieve here (see Listing 2.59) a linear ranking without ties (from best to worst) of the digraph's actions set, i.e. including the new decision alternatives as well as the quartile limits m_1 to m_4 , which is very close in an ordinal sense ($\tau = 0.945$) to the underlying strict outranking relation.

The eventual rating procedure is based in this example on the *lower* quartile limits, such that we may collect the quartile classes' contents in increasing order of the *quartiles*.

```

1 >>> lqr.ratingCategories
2   OrderedDict([

```

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```
3 ('m2', ['a1007','a1004','a1009']),
4 ('m3', ['a1005','a1010','a1002','a1008','a1006','a1001','a1003'])
5 ])
```

We notice above that no new decision alternatives are actually rated in the lowest [0.0-0.25[, respectively highest [0.75- [quartile classes. Indeed, the rating result is shown, in descending order, as follows:

Listing 2.60: Showing a quantiles rating result

```
1 >>> lqr.showRatingByQuantilesRanking()
2 ----- rating by quantiles ranking result -----
3 [0.50 - 0.75[ ['a1005', 'a1010', 'a1002', 'a1008',
4           'a1006', 'a1001', 'a1003']
5 [0.25 - 0.50[ ['a1004', 'a1007', 'a1009']]
```

The same result may more conveniently be consulted in a browser view via a specialised rating heatmap format (see `showHTMLPerformanceHeatmap()` method (see Fig. 2.22).

```
1 >>> lqr.showHTMLRatingHeatmap(
2             pageTitle='Heatmap of Quartiles Rating',
3             Correlations=True,colorLevels=5)
```

Heatmap of Quartiles Rating

Ranking rule: Copeland; Ranking correlation: **0.938**

criteria	c2	b3	c1	b4	b1	b2	b5
weights	5	2	5	2	2	2	2
tau(*)	+0.64	+0.54	+0.43	+0.37	+0.37	+0.35	+0.34
[0.75 -]	-30.00	7.00	-3.00	70.89	70.73	7.00	69.98
a1005c	-24.00	6.00	-1.00	28.00	42.00	3.00	30.00
a1010n	-35.00	6.00	-4.00	55.00	32.00	9.00	51.00
a1002c	-23.00	4.00	-6.00	54.00	27.00	5.00	63.00
a1008n	-43.00	6.00	-6.00	49.00	64.00	5.00	96.00
a1006c	-27.00	3.00	-5.00	20.00	33.00	3.00	39.00
a1001c	-40.00	2.00	-4.00	61.00	37.00	2.00	31.00
a1003a	-37.00	2.00	-8.00	74.00	24.00	8.00	61.00
[0.50 -]	-50.10	5.00	-5.00	50.82	49.44	5.00	48.55
a1007c	-73.00	2.00	-1.00	20.00	39.00	6.00	16.00
a1004c	-37.00	1.00	-5.00	25.00	16.00	3.00	48.00
a1009n	-94.00	6.00	-6.00	44.00	42.00	4.00	57.00
[0.25 -]	-70.65	3.00	-7.00	30.10	29.82	3.00	29.08
[0.00 -]	-96.37	0.00	-10.00	3.27	1.99	0.00	0.85

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
-----------------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation.

Fig. 2.22: Heatmap of absolute quartiles ranking

Using furthermore a specialised version of the `exportGraphViz()` method allows drawing the same rating result in a Hasse diagram format (see Fig. 2.23).

```

1 >>> lqr.exportRatingByRankingGraphViz('normedRatingDigraph')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to normedRatingDigraph.dot
4 dot -Grankdir=TB -Tpng normedRatingDigraph.dot -o normedRatingDigraph.
   ↵png

```

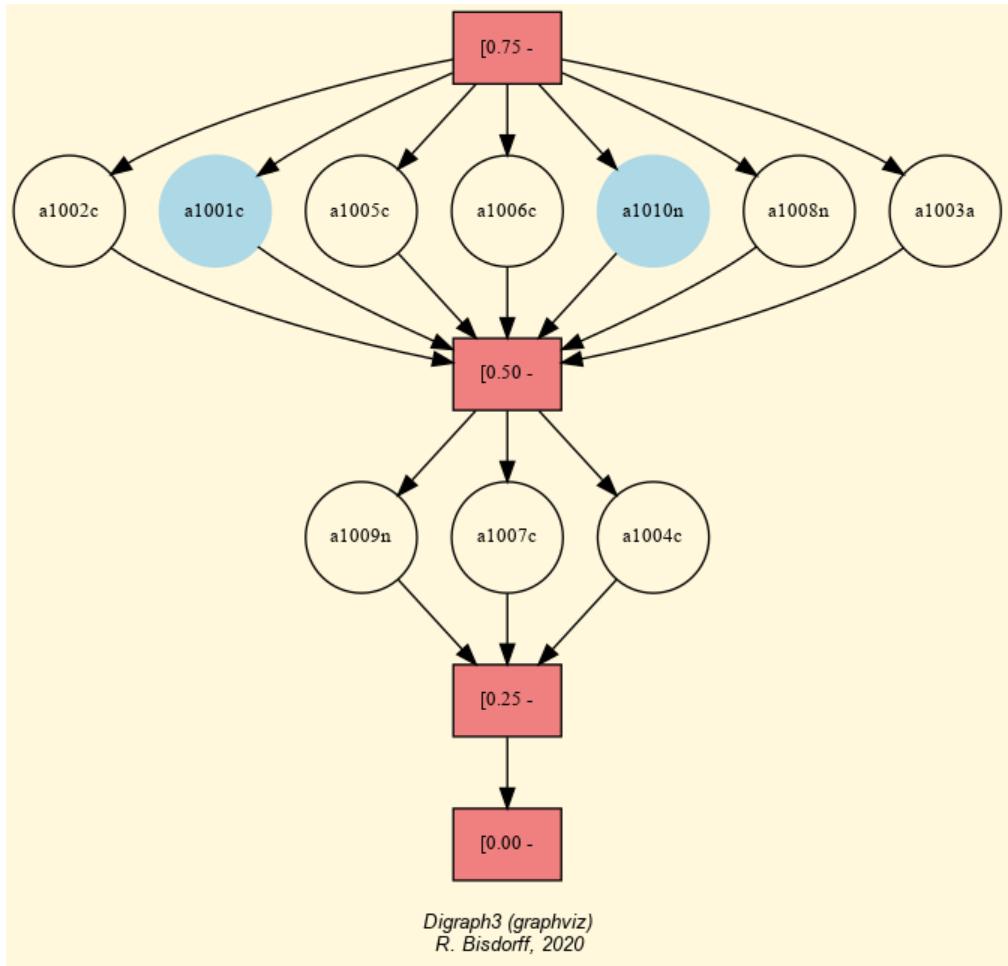


Fig. 2.23: Absolute quartiles rating digraph

We may now answer the **absolute rating decision problem** stated at the beginning. Decision alternative $a1001$ and alternative $a1010$ (see below) are both rated into the same quartile **Q3** class (see Fig. 2.23), even if the *Copeland* ranking, obtained from the underlying strict outranking digraph (see Fig. 2.22), suggests that alternative $a1010$ is effectively *better performing than* alternative $a1001$.

Criterion	b1	b2	b3	b4	b5	c1	c2
weight	2	2	2	2	2	5	5
$a1001$	37.0	2	2	61.0	31.0	-4	-40.0
$a1010$	32.0	9	6	55.0	51.0	-4	-35.0

A preciser rating result may indeed be achieved when using **deciles** instead of *quartiles* for estimating the historical marginal cumulative distribution functions.

Listing 2.61: Absolute deciles rating result

```

1 >>> pq1 = PerformanceQuantiles(tp, number0fBins = 'deciles',
2                                LowerClosed=True)

```

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```
3
4 >>> pq1.updateQuantiles(newTab, historySize=None)
5 >>> lqr1 = RatingByLearnedQuantilesDigraph(pq1, newActions, rankingRule=
6     ↪ 'best')
7 >>> lqr1.showRatingByQuantilesRanking()
8 *----- Deciles rating result -----
9 [0.60 - 0.70[ ['a1005', 'a1010', 'a1008', 'a1002']
10 [0.50 - 0.60[ ['a1006', 'a1001', 'a1003']
11 [0.40 - 0.50[ ['a1007', 'a1004']
12 [0.30 - 0.40[ ['a1009']]
```

Compared with the quartiles rating result, we notice in Listing 2.61 that the seven alternatives ($a1001, a1002, a1003, a1005, a1006, a1008$ and $a1010$), rated before into the third quartile class $[0.50-0.75]$, are now divided up: alternatives $a1002, a1005, a1008$ and $a1010$ attain now the 7th decile class $[0.60-0.70]$, whereas alternatives $a1001, a1003$ and $a1006$ attain only the 6th decile class $[0.50-0.60]$. Of the three $Q2$ $[0.25-0.50]$ rated alternatives ($a1004, a1007$ and $a1009$), alternatives $a1004$ and $a1007$ are now rated into the 5th decile class $[0.40-0.50]$ and $a1009$ is lowest rated into the 4th decile class $[0.30-0.40]$.

A browser view may again more conveniently illustrate this refined rating result (see Fig. 2.24).

```
1 >>> lqr1.showHTMLRatingHeatmap(
2 ...     pageTitle='Heatmap of the deciles rating',
3 ...     colorLevels=5, Correlations=True)
```

Heatmap of Deciles rating

Ranking rule: NetFlows; Ranking correlation: **0.960**

criteria	c2	b3	c1	b1	b5	b2	b4
weights	5	2	5	2	2	2	2
tau(*)	0.67	0.65	0.58	0.57	0.53	0.53	0.48
[0.90 -]	-20.32	7.73	-2.53	86.83	82.16	7.66	82.04
[0.80 -]	-29.70	7.26	-3.35	79.30	75.15	6.64	74.66
[0.70 -]	-37.97	6.67	-4.14	70.95	60.20	5.88	69.76
a1005c	-24.00	6.00	-1.00	42.00	30.00	3.00	28.00
a1010n	-35.00	6.00	-4.00	32.00	51.00	9.00	55.00
a1008n	-43.00	6.00	-6.00	64.00	96.00	5.00	49.00
a1002c	-23.00	4.00	-6.00	27.00	63.00	5.00	54.00
[0.60 -]	-44.23	5.92	-5.04	60.56	56.01	5.37	62.23
a1006c	-27.00	3.00	-5.00	33.00	39.00	3.00	20.00
a1001c	-40.00	2.00	-4.00	37.00	31.00	2.00	61.00
a1003a	-37.00	2.00	-8.00	24.00	61.00	8.00	74.00
[0.50 -]	-52.22	4.64	-6.02	49.56	48.07	4.83	58.45
a1007c	-73.00	2.00	-1.00	39.00	16.00	6.00	20.00
a1004c	-37.00	1.00	-5.00	16.00	48.00	3.00	25.00
[0.40 -]	-60.50	3.84	-6.69	39.61	40.16	4.25	49.82
a1009n	-94.00	6.00	-6.00	42.00	57.00	4.00	44.00
[0.30 -]	-67.14	3.12	-7.32	30.85	34.33	3.30	40.89
[0.20 -]	-77.07	2.55	-7.94	23.84	29.57	2.27	30.45
[0.10 -]	-83.04	1.99	-8.48	16.64	16.91	1.58	24.78
[0.00 -]	-96.37	0.00	-10.00	1.99	0.85	0.00	3.27

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
-----------------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation.

Fig. 2.24: Heatmap of absolute deciles rating

In this *deciles* rating, decision alternatives *a1001* and *a1010* are now, as expected, rated in the 6th decile (D6), respectively in the 7th decile (D7).

To avoid having to recompute performance deciles from historical data when wishing to refine a rating result, it is useful, depending on the actual size of the historical data, to initially compute performance quantiles with a relatively high number of bins, for instance *dodeciles* or *centiles*. It is then possible to correctly interpolate *quartiles* or *deciles* for instance, when constructing the rating digraph.

Listing 2.62: From deciles interpolated quartiles rating result

```
1 >>> lqr2 = RatingByLearnedQuantilesDigraph(pq1,newActions,
2 ...           quantiles='quartiles')
3 >>> lqr2.showRatingByQuantilesRanking()
4 ----- Deciles rating result -----
5 [0.50 - 0.75[ ['a1005', 'a1010', 'a1002', 'a1008',
6           'a1006', 'a1001', 'a1003']
7 [0.25 - 0.50[ ['a1004', 'a1007', 'a1009']
```

With the *quantiles* parameter (see Listing 2.62 Line 2), we may recover by interpolation the same quartiles rating as obtained directly with historical performance quartiles (see Listing 2.60). Mind that a correct interpolation of quantiles from a given cumulative distribution function requires more or less uniform distributions of observations in each bin.

More generally, in the case of industrial production monitoring problems, for instance, where large volumes of historical performance data may be available, it may be of interest to estimate even more precisely the marginal cumulative distribution functions, especially when **tail** rating results, i.e. distinguishing **very best**, or **very worst** multiple criteria performances, become a critical issue. Similarly, the *historySize* parameter may be used for monitoring on the fly **unstable** random multiple criteria performance data.

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2.8 Computing the winner of an election with the `votingProfiles` module

- *Linear voting profiles* (page 129)
- *Computing the winner* (page 131)
- *The Condorcet winner* (page 132)
- *Cyclic social preferences* (page 134)
- *On generating realistic random linear voting profiles* (page 136)

Linear voting profiles

The `votingProfiles` module provides resources for handling election results [ADT-L2], like the `LinearVotingProfile` class. We consider an election involving a finite set of candidates and finite set of weighted voters, who express their voting preferences in a complete linear ranking (without ties) of the candidates. The data is internally stored in two ordered dictionaries, one for the voters and another one for the candidates. The linear ballots are stored in a standard dictionary.

```

1 candidates = OrderedDict([('a1',...), ('a2',...), ('a3', ...), ...]
2 voters = OrderedDict([('v1',{'weight':10}), ('v2',{'weight':3}), ...]
3 ## each voter specifies a linearly ranked list of candidates
4 ## from the best to the worst (without ties)
5 linearBallot = {
6   'v1' : ['a2','a3','a1', ...],
7   'v2' : ['a1','a2','a3', ...],
8   ...
9 }
```

The module provides a `RandomLinearVotingProfile` class for generating random instances of the `LinearVotingProfile` class. In an interactive Python session we may obtain for the election of 3 candidates by 5 voters the following result.

Listing 2.63: Example of random linear voting profile

```

1 >>> from votingProfiles import RandomLinearVotingProfile
2 >>> v = RandomLinearVotingProfile(numberOfVoters=5,
3 ...                               numberOfCandidates=3,
4 ...                               RandomWeights=True)
5
6 >>> v.candidates
7 OrderedDict([('a1',{'name':'a1'}), ('a2',{'name':'a2'}),
8             ('a3',{'name':'a3'})])
9 >>> v.voters
10 OrderedDict([('v1',{'weight': 2}), ('v2':{'weight': 3}),
11              ('v3',{'weight': 1}), ('v4':{'weight': 5}),
12              ('v5',{'weight': 4})])
13 >>> v.linearBallot
14 {'v1': ['a1', 'a2', 'a3'],
15  'v2': ['a3', 'a2', 'a1'],
16  'v3': ['a1', 'a3', 'a2'],
17  'v4': ['a1', 'a3', 'a2'],
18  'v5': ['a2', 'a3', 'a1']}
```

Notice that in this random example, the five voters are weighted (see Listing 2.63 Lines 10-12). Their linear ballots can be viewed with the `showLinearBallots()` method.

```

1 >>> v.showLinearBallots()
2 voters(weight)      candidates rankings
3 v1(2):          ['a2', 'a1', 'a3']
4 v2(3):          ['a3', 'a1', 'a2']
5 v3(1):          ['a1', 'a3', 'a2']
6 v4(5):          ['a1', 'a2', 'a3']
7 v5(4):          ['a3', 'a1', 'a2']
8 # voters: 15
```

Editing of the linear voting profile may be achieved by storing the data in a file, edit it,

and reload it again.

```
1 >>> v.save(fileName='tutorialLinearVotingProfile1')
2     ---- Saving linear profile in file: <tutorialLinearVotingProfile1.py> --
3     -->
4 >>> from votingProfiles import LinearVotingProfile
>>> v = LinearVotingProfile('tutorialLinearVotingProfile1')
```

Computing the winner

We may easily compute **uni-nominal votes**, i.e. how many times a candidate was ranked first, and see who is consequently the **simple majority** winner(s) in this election.

```
1 >>> v.computeUninominalVotes()
2     {'a2': 2, 'a1': 6, 'a3': 7}
3 >>> v.computeSimpleMajorityWinner()
4     ['a3']
```

As we observe no absolute majority ($8/15$) of votes for any of the three candidate, we may look for the **instant runoff** winner instead (see [ADT-L2]).

Listing 2.64: Example Instant Run Off Winner

```
1 >>> v.computeInstantRunoffWinner(Comments=True)
2     Half of the Votes = 7.50
3     ==> stage = 1
4         remaining candidates ['a1', 'a2', 'a3']
5         uninominal votes {'a1': 6, 'a2': 2, 'a3': 7}
6         minimal number of votes = 2
7         maximal number of votes = 7
8         candidate to remove = a2
9         remaining candidates = ['a1', 'a3']
10    ==> stage = 2
11    remaining candidates ['a1', 'a3']
12    uninominal votes {'a1': 8, 'a3': 7}
13    minimal number of votes = 7
14    maximal number of votes = 8
15    candidate a1 obtains an absolute majority
16    Instant run off winner: ['a1']
```

In stage 1, no candidate obtains an absolute majority of votes. Candidate $a2$ obtains the minimal number of votes ($2/15$) and is, hence, eliminated. In stage 2, candidate $a1$ obtains an absolute majority of the votes ($8/15$) and is eventually elected (see Listing 2.64).

We may also follow the *Chevalier de Borda*'s advice and, after a **rank analysis** of the linear ballots, compute the **Borda score** -the average rank- of each candidate and hence determine the **Borda winner(s)**.

Listing 2.65: Example of *Borda* rank scores

```

1 >>> v.computeRankAnalysis()
2 {'a2': [2, 5, 8], 'a1': [6, 9, 0], 'a3': [7, 1, 7]}
3 >>> v.computeBordaScores()
4 OrderedDict([
5     ('a1', {'BordaScore': 24, 'averageBordaScore': 1.6}),
6     ('a3', {'BordaScore': 30, 'averageBordaScore': 2.0}),
7     ('a2', {'BordaScore': 36, 'averageBordaScore': 2.4}) ])
8 >>> v.computeBordaWinners()
9 ['a1']

```

Candidate a_1 obtains the minimal *Borda* score, followed by candidate a_3 and finally candidate a_2 (see Listing 2.65). The corresponding ***Borda* rank analysis table** may be printed out with a corresponding `show()` command.

Listing 2.66: Rank analysis example

```

1 >>> v.showRankAnalysisTable()
2 *----- Borda rank analysis tableau -----*
3 candi- | alternative-to-rank |      Borda
4 dates  |    1      2      3      | score   average
5 -----|-----|-----|-----|-----|
6 'a1'   |    6      9      0      | 24/15   1.60
7 'a3'   |    7      1      7      | 30/15   2.00
8 'a2'   |    2      5      8      | 36/15   2.40

```

In our randomly generated election results, we are lucky: The instant runoff winner and the *Borda* winner both are candidate a_1 (see Listing 2.64 and Listing 2.66). However, we could also follow the *Marquis de Condorcet*'s advice, and compute the **majority margins** obtained by voting for each individual pair of candidates.

The *Condorcet* winner

For instance, candidate a_1 is ranked four times before and once behind candidate a_2 . Hence the corresponding **majority margin** $M(a_1, a_2)$ is $4 - 1 = +3$. These *majority margins* define on the set of candidates what we call the **majority margins digraph**. The `MajorityMarginsDigraph` class (a specialization of the `Digraph` class) is available for handling such kind of digraphs.

Listing 2.67: Example of *Majority Margins* digraph

```

1 >>> from votingProfiles import MajorityMarginsDigraph
2 >>> cdg = MajorityMarginsDigraph(v, IntegerValuation=True)
3 >>> cdg
4 *----- Digraph instance description -----*
5 Instance class      : MajorityMarginsDigraph
6 Instance name       : rel_randomLinearVotingProfile1

```

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```

7 Digraph Order      : 3
8 Digraph Size       : 3
9 Valuation domain   : [-15.00;15.00]
10 Determinateness (%) : 64.44
11 Attributes        : ['name', 'actions', 'voters',
12                           'ballot', 'valuationdomain',
13                           'relation', 'order',
14                           'gamma', 'notGamma']
15 >>> cdg.showAll()
16 ----- show detail -----
17 Digraph          : rel_randLinearVotingProfile1
18 ----- Actions ----*
19 ['a1', 'a2', 'a3']
20 ----- Characteristic valuation domain ----*
21 {'max': Decimal('15.0'), 'med': Decimal('0'),
22  'min': Decimal('-15.0'), 'hasIntegerValuation': True}
23 * ----- majority margins -----
24 M(x,y) | 'a1'  'a2'  'a3'
25 -----|-----
26 'a1'  | 0    11    1
27 'a2'  | -11   0    -1
28 'a3'  | -1    1     0
29 Valuation domain: [-15;+15]
```

Notice that in the case of linear voting profiles, majority margins always verify a zero sum property: $M(x,y) + M(y,x) = 0$ for all candidates x and y (see Listing 2.67 Lines 26-28). This is not true in general for arbitrary voting profiles. The *majority margins* digraph of linear voting profiles defines in fact a *weak tournament* and belongs, hence, to the class of *self-codual* bipolar-valued digraphs (13).

Now, a candidate x , showing a positive majority margin $M(x,y)$, is beating candidate y with an absolute majority in a pairwise voting. Hence, a candidate showing only positive terms in her row in the *majority margins* digraph relation table, beats all other candidates with absolute majority of votes. *Condorcet* recommends to declare this candidate (is always unique, why?) the winner of the election. Here we are lucky, it is again candidate $a1$ who is hence the **Condorcet winner** (see Listing 2.67 Line 26).

```

1 >>> cdg.computeCondorcetWinners()
2 ['a1']
```

By seeing the majority margins like a *bipolar-valued characteristic function* of a global preference relation defined on the set of candidates, we may use all operational resources of the generic **Digraph** class (see *Working with the Digraph3 software resources* (page 2)),

¹³ The class of *self-codual* bipolar-valued digraphs consists of all *weakly asymmetrical* digraphs, i.e. digraphs containing only *asymmetrical* and/or *indeterminate* links. Limit cases consists of, on the one side, *full tournaments* with *indeterminate reflexive links*, and, on the other side, *fully indeterminate* digraphs. In this class, the *converse* (inverse \sim) operator is indeed identical to the *dual* (negation $-$) one.

and especially its `exportGraphViz()` method^{Page 7, 1}, for visualizing an election result.

```

1 >>> cdg.exportGraphViz(fileName='tutorialLinearBallots')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to tutorialLinearBallots.dot
4 dot -Grankdir=BT -Tpng tutorialLinearBallots.dot -o
  ↳tutorialLinearBallots.png

```

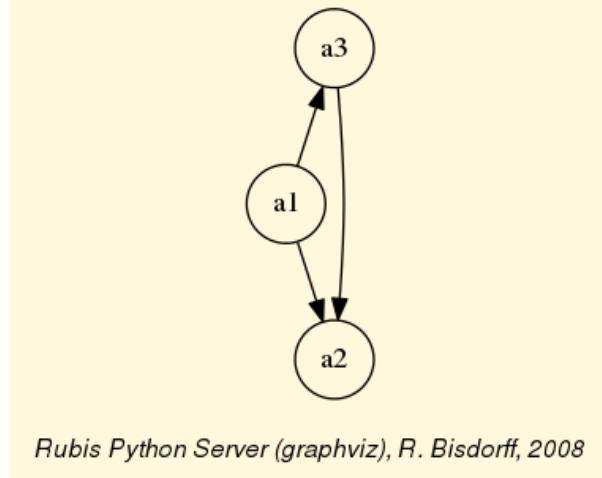


Fig. 2.25: Visualizing an election result

In Fig. 2.25 we notice that the *majority margins* digraph from our example linear voting profile gives a linear order of the candidates: ['a1', 'a3', 'a2], the same actually as given by the *Borda* scores (see Listing 2.65). This is by far not given in general. Usually, when aggregating linear ballots, there appear cyclic social preferences.

Cyclic social preferences

Let us consider for instance the following linear voting profile and construct the corresponding majority margins digraph.

Listing 2.68: Example of cyclic social preferences

```

1 >>> v.showLinearBallots()
2 voters(weight)      candidates rankings
3 v1(1):      ['a1', 'a3', 'a5', 'a2', 'a4']
4 v2(1):      ['a1', 'a2', 'a4', 'a3', 'a5']
5 v3(1):      ['a5', 'a2', 'a4', 'a3', 'a1']
6 v4(1):      ['a3', 'a4', 'a1', 'a5', 'a2']
7 v5(1):      ['a4', 'a2', 'a3', 'a5', 'a1']
8 v6(1):      ['a2', 'a4', 'a5', 'a1', 'a3']
9 v7(1):      ['a5', 'a4', 'a3', 'a1', 'a2']
10 v8(1):     ['a2', 'a4', 'a5', 'a1', 'a3']
11 v9(1):     ['a5', 'a3', 'a4', 'a1', 'a2']
12 >>> cdg = MajorityMarginsDigraph(v)

```

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```

13 >>> cdg.showRelationTable()
14 * ----- Relation Table -----
15   S | 'a1'  'a2'  'a3'  'a4'  'a5'
16   -+-----+
17 'a1' |   -    0.11 -0.11 -0.56 -0.33
18 'a2' | -0.11   -    0.11  0.11 -0.11
19 'a3' |  0.11 -0.11   -    -0.33 -0.11
20 'a4' |  0.56 -0.11  0.33   -    0.11
21 'a5' |  0.33  0.11  0.11 -0.11   -

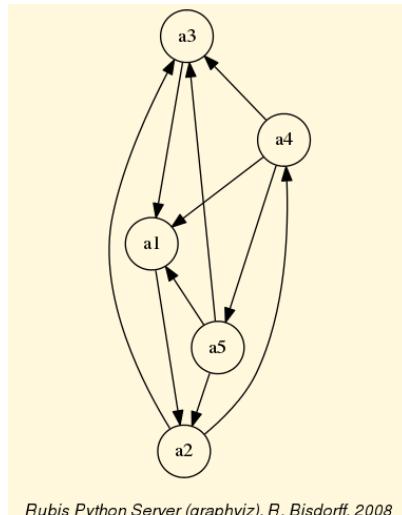
```

Now, we cannot find any completely positive row in the relation table (see Listing 2.68 Lines 17 -). No one of the five candidates is beating all the others with an absolute majority of votes. There is no *Condorcet* winner anymore. In fact, when looking at a graphviz drawing of this *majority margins* digraph, we may observe *cyclic* preferences, like $(a_1 > a_2 > a_3 > a_1)$ for instance (see Fig. 2.26).

```

1 >>> cdg.exportGraphViz('cycles')
2 *----- exporting a dot file for GraphViz tools -----*
3 Exporting to cycles.dot
4 dot -Grankdir=BT -Tpng cycles.dot -o cycles.png

```



Rubis Python Server (graphviz), R. Bisdorff, 2008

Fig. 2.26: Cyclic social preferences

But, there may be many cycles appearing in a *majority margins* digraph, and, we may detect and enumerate all minimal chordless circuits in a Digraph instance with the `computeChordlessCircuits()` method.

```

1 >>> cdg.computeChordlessCircuits()
2 [(['a2', 'a3', 'a1'], frozenset({'a2', 'a3', 'a1'})),
3  ('[a2', 'a4', 'a5'], frozenset({'a2', 'a5', 'a4'})),
4  ('[a2', 'a4', 'a1'], frozenset({'a2', 'a1', 'a4'}))]

```

Condorcet ‘s approach for determining the winner of an election is hence *not decisive* in all circumstances and we need to exploit more sophisticated approaches for finding the winner of the election on the basis of the majority margins of the given linear ballots (see the tutorial on *ranking with multiple incommensurable criteria* (page 82) and [BIS-2008]).

Many more tools for exploiting voting results are available like the browser heat map view on voting profiles (see the technical documentation of the `votingProfiles` module).

Listing 2.69: Example linear voting heatmap

```

1 :linenos:
2
3 >>> v.showHTMLVotingHeatmap(rankingRule='NetFlows',
4 ...                                     Transposed=False)

```

Voting Heatmap

criteria	v5	v3	v8	v7	v6	v9	v4	v2	v1
weights	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00	-1.00
tau(*)	+0.60	+0.60	+0.40	+0.40	+0.40	+0.20	+0.00	-0.40	-0.80
a4	1	3	2	2	2	3	2	3	5
a5	4	1	3	1	3	1	4	5	3
a2	2	2	1	5	1	5	5	2	4
a3	3	4	5	3	5	2	1	4	2
a1	5	5	4	4	4	4	3	1	1

Color legend:

quantile	14.29%	28.57%	42.86%	57.14%	71.43%	85.71%	100.00%
----------	--------	--------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation

Ranking rule: NetFlows

Ordinal (Kendall) correlation between global ranking and global outranking relation: +0.778

Fig. 2.27: Visualizing a linear voting profile in a heatmap format

Notice that the importance weights of the voters are *negative*, which means that the preference direction of the criteria (in this case the individual voters) is *decreasing*, i.e. goes from lowest (best) rank to highest (worst) rank. Notice also, that the compromise *NetFlows* ranking $[a_4, a_5, a_2, a_1, a_3]$, shown in this heatmap (see Fig. 2.27) results in an optimal *ordinal correlation* index of +0.778 with the pairwise majority voting margins (see the Advanced topic on Ordinal Correlation equals Relational Equivalence and *Linearly ranking with multiple incommensurable criteria* (page 82)). The number of voters is usually much larger than the number of candidates. In that case, it is better to generate a transposed *voters X candidates* view (see Listing 2.69 Line 2)

On generating realistic random linear voting profiles

By default, the `RandomLinearVotingProfile` class generates random linear voting profiles where every candidate has the same uniform probabilities to be ranked at a certain position by all the voters. For each voter’s random linear ballot is indeed generated via a uniform shuffling of the list of candidates.

In reality, political election data appear quite different. There will usually be different favorite and marginal candidates for each political party. To simulate these aspects into our random generator, we are using two random exponentially distributed polls of the candidates and consider a bipartisan political landscape with a certain random balance (default theoretical party repartition = 0.50) between the two sets of potential party supporters (see `LinearVotingProfile` class). A certain theoretical proportion (default = 0.1) will not support any party.

Let us generate such a linear voting profile for an election with 1000 voters and 15 candidates.

Listing 2.70: Generating a linear voting profile with random polls

```

1  >>> from votingProfiles import RandomLinearVotingProfile
2  >>> lvp = RandomLinearVotingProfile(numberOfCandidates=15,
3  ...                               numberOfVoters=1000,
4  ...                               WithPolls=True,
5  ...                               partyRepartition=0.5,
6  ...                               other=0.1,
7  ...                               seed=0.9189670954954139)
8
9  >>> lvp
10 *----- VotingProfile instance description -----*
11 Instance class    : RandomLinearVotingProfile
12 Instance name     : randLinearProfile
13 # Candidates      : 15
14 # Voters          : 1000
15 Attributes        : ['name', 'seed', 'candidates',
16                      'voters', 'RandomWeights',
17                      'sumWeights', 'poll1', 'poll2',
18                      'bipartisan', 'linearBallot', 'ballot']
19 >>> lvp.showRandomPolls()
20 Random repartition of voters
21 Party_1 supporters : 460 (46.0%)
22 Party_2 supporters : 436 (43.6%)
23 Other voters       : 104 (10.4%)
24 *----- random polls -----*
25 Party_1(46.0%) | Party_2(43.6%)| expected
26 -----
27   a06 : 19.91% | a11 : 22.94% | a06 : 15.00%
28   a07 : 14.27% | a08 : 15.65% | a11 : 13.08%
29   a03 : 10.02% | a04 : 15.07% | a08 : 09.01%
30   a13 : 08.39% | a06 : 13.40% | a07 : 08.79%
31   a15 : 08.39% | a03 : 06.49% | a03 : 07.44%
32   a11 : 06.70% | a09 : 05.63% | a04 : 07.11%
33   a01 : 06.17% | a07 : 05.10% | a01 : 05.06%
34   a12 : 04.81% | a01 : 05.09% | a13 : 05.04%
```

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35	a08 : 04.75%		a12 : 03.43%		a15 : 04.23%
36	a10 : 04.66%		a13 : 02.71%		a12 : 03.71%
37	a14 : 04.42%		a14 : 02.70%		a14 : 03.21%
38	a05 : 04.01%		a15 : 00.86%		a09 : 03.10%
39	a09 : 01.40%		a10 : 00.44%		a10 : 02.34%
40	a04 : 01.18%		a05 : 00.29%		a05 : 01.97%
41	a02 : 00.90%		a02 : 00.21%		a02 : 00.51%

In this example (see Listing 2.70 Lines 19-), we obtain 460 *Party_1* supporters (46%), 436 *Party_2* supporters (43.6%) and 104 other voters (10.4%). Favorite candidates of *Party_1* supporters, with more than 10%, appear to be *a06* (19.91%), *a07* (14.27%) and *a03* (10.02%). Whereas for *Party_2* supporters, favorite candidates appear to be *a11* (22.94%), followed by *a08* (15.65%), *a04* (15.07%) and *a06* (13.4%). Being *first* choice for *Party_1* supporters and *fourth* choice for *Party_2* supporters, this candidate *a06* is a natural candidate for clearly winning this election game (see Listing 2.71).

Listing 2.71: The uninominal election winner

```

1 >>> lvp.computeSimpleMajorityWinner()
2 ['a06']
3 >>> lvp.computeInstantRunoffWinner()
4 ['a06']
5 >>> lvp.computeBordaWinners()
6 ['a06']

```

Is it also a *Condorcet* winner? To verify, we start by creating the corresponding *majority margins* digraph *cdg* with the help of the *MajorityMarginsDigraph* class. The created digraph instance contains 15 *actions*-the candidates- and 105 oriented arcs -the *positive* majority margins- (see Listing 2.72 Lines 7-8).

Listing 2.72: A majority margins digraph constructed from a linear voting profile

```

1 >>> from votingProfiles import MajorityMarginsDigraph
2 >>> cdg = MajorityMarginsDigraph(lvp)
3 >>> cdg
4 *----- Digraph instance description -----*
5 Instance class      : MajorityMarginsDigraph
6 Instance name       : rel_randLinearProfile
7 Digraph Order       : 15
8 Digraph Size        : 104
9 Valuation domain    : [-1000.00;1000.00]
10 Determinateness (%) : 67.08
11 Attributes          : ['name', 'actions', 'voters',
12                           'ballot', 'valuationdomain',
13                           'relation', 'order',
14                           'gamma', 'notGamma']

```

We may visualize the resulting pairwise majority margins by showing the HTML formated version of the *cdg* relation table in a browser view.

```
>>> cdg.showHTMLRelationTable(tableTitle='Pairwise majority margins',
...                                relationName='M(x>y)')
```

Pairwise majority margins

M(x>y)	a01	a02	a03	a04	a05	a06	a07	a08	a09	a10	a11	a12	a13	a14	a15
a01	-	768	-138	108	478	-436	-198	-140	238	440	-268	148	50	202	218
a02	-768	-	-796	-484	-368	-858	-828	-772	-546	-496	-800	-722	-768	-696	-658
a03	138	796	-	160	590	-286	-80	-8	372	522	-158	280	210	360	338
a04	-108	484	-160	-	184	-370	-180	-288	160	136	-420	16	-62	56	30
a05	-478	368	-590	-184	-	-730	-640	-472	-234	-116	-550	-442	-522	-376	-386
a06	436	858	286	370	730	-	248	234	574	692	102	556	482	566	520
a07	198	828	80	180	640	-248	-	0	358	602	-94	304	266	384	420
a08	140	772	8	288	472	-234	0	-	436	396	-176	276	134	298	244
a09	-238	546	-372	-160	234	-574	-358	-436	-	116	-594	-126	-194	-90	-14
a10	-440	496	-522	-136	116	-692	-602	-396	-116	-	-510	-310	-442	-304	-266
a11	268	800	158	420	550	-102	94	176	594	510	-	388	268	474	292
a12	-148	722	-280	-16	442	-556	-304	-276	126	310	-388	-	-92	100	148
a13	-50	768	-210	62	522	-482	-266	-134	194	442	-268	92	-	158	186
a14	-202	696	-360	-56	376	-566	-384	-298	90	304	-474	-100	-158	-	68
a15	-218	658	-338	-30	386	-520	-420	-244	14	266	-292	-148	-186	-68	-

Valuation domain: [-1000; +1000]

Fig. 2.28: Browsing the majority margins

In Fig. 2.28, *light green* cells contain the positive majority margins, whereas *light red* cells contain the negative majority margins. A complete *light green* row reveals hence a *Condorcet winner*, whereas a complete *light green* column reveals a *Condorcet loser*. We recover again candidate *a06* as *Condorcet* winner⁽¹⁵⁾, whereas the obvious *Condorcet* loser is here candidate *a02*, the candidate with the lowest support in both parties (see Listing 2.70 Line 40).

With a same *bipolar -first ranked* and *last ranked* candidate- selection procedure, we may *weakly rank* the candidates (with possible ties) by iterating these *first ranked* and *last ranked* choices among the remaining candidates ([BIS-1999]).

Listing 2.73: Ranking by iterating choosing the *first* and *last* remaining candidates

```
1  >>> cdg.showRankingByChoosing()
2  Error: You must first run
3      self.computeRankingByChoosing(CoDual=False(default)|True) !
4  >>> cdg.computeRankingByChoosing()
5  >>> cdg.showRankingByChoosing()
```

(continues on next page)

¹⁵ The concept of *Condorcet* winner -a generalization of absolute majority winners- proposed by *Condorcet* in 1785, is an early historical example of *initial* digraph kernel (see the tutorial Kernel-Tutorial-label).

```

6 Ranking by Choosing and Rejecting
7 1st first ranked ['a06']
8 2nd first ranked ['a11']
9 3rd first ranked ['a07', 'a08']
10 4th first ranked ['a03']
11 5th first ranked ['a01']
12 6th first ranked ['a13']
13 7th first ranked ['a04']  

14 7th last ranked ['a12']
15 6th last ranked ['a14']
16 5th last ranked ['a15']
17 4th last ranked ['a09']
18 3rd last ranked ['a10']
19 2nd last ranked ['a05']
20 1st last ranked ['a02']

```

Before showing the *ranking-by-choosing* result, we have to compute the iterated bipolar selection procedure (see Listing 2.73 Line 2). The first selection concerns *a06* (first) and *a02* (last), followed by *a11* (first) opposed to *a05* (last), and so on, until there remains at iteration step 7 a last pair of candidates, namely [*a04*, *a12*] (see Lines 13-14).

Notice furthermore the first ranked candidates at iteration step 3 (see Listing 2.73 Line 9), namely the pair [*a07*, *a08*]. Both candidates represent indeed conjointly the *first ranked* choice. We obtain here hence a *weak ranking*, i.e. a ranking with a tie.

Let us mention that the *instant-run-off* procedure, we used before (see Listing 2.71 Line 3), when operated with a *Comments=True* parameter setting, will deliver a more or less similar *reversed linear ordering-by-rejecting* result, namely [*a02*, *a10*, *a14*, *a05*, *a09*, *a13*, *a12*, *a15*, *a04*, *a01*, *a08*, *a03*, *a07*, *a11*, *a06*], ordered from the *last* to the *first* choice.

Remarkable about both these *ranking-by-choosing* or *ordering-by-rejecting* results is the fact that the random voting behaviour, simulated here with the help of two discrete random variables ^{[\(16\)](#)}, defined respectively by the two party polls, is rendering a ranking that is more or less in accordance with the simulated balance of the polls: *-Party_1* supporters : 460; *Party_2* supporters: 436 (see Listing 2.70 Lines 26-40 third column). Despite a random voting behaviour per voter, the given polls apparently show a *very strong incidence* on the eventual election result. In order to avoid any manipulation of the election outcome, public media are therefore in some countries not allowed to publish polls during the last weeks before a general election.

Note

Mind that the specific *ranking-by-choosing* procedure, we use here on the *majority margins* digraph, operates the selection procedure by extracting at each step *initial* and *terminal* kernels, i.e. NP-hard operational problems (see tutorial on computing

¹⁶ Discrete random variables with a given empirical probability law (here the polls) are provided in the `randomNumbers` module by the `DiscreteRandomVariable` class.

kernels and [BIS-1999]); A technique that does not allow in general to tackle voting profiles with much more than 30 candidates. The tutorial on *ranking* (page 82) provides more adequate and efficient techniques for ranking from pairwise majority margins when a larger number of potential candidates is given.

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2.9 On computing fair intergroup pairings

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- *Generating the set of potential maximal matchings* (page 143)
- *Measuring the fitness of a matching from a personal perspective* (page 144)
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- *Fair versus stable pairings* (page 149)
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The fair intergroup pairing problem

Fairness: *impartial and just treatment or behaviour without favouritism or discrimination* – Oxford Languages

A set of persons consists of two groups –group A and group B – of equal size k . For a social happening, it is requested to build k pairs of persons from each group.

In order to guide the matching decisions, each person of group A communicates her pairing preferences with a linear ranking of the persons in group B and each person of group B communicates her pairing preferences with a linear ranking of the persons in group A .

The set of all potential matching decisions corresponds to the set of maximal matchings of the complete bipartite graph formed by the two groups A and B . Its cardinality is factorial k .

How to choose now in this possibly huge set the one maximal matching that makes a fair balance of the given individual pairing preferences? To help make this decision we will compute for all maximal matchings a fitness score consisting of their average ordinal correlation index with the given marginal pairing preferences. Eventually we will choose a maximal matching that results in the highest possible fitness score.

Let us consider for instance a set of four persons divided into group A, $\{a_1, a_2\}$, and group B, $\{b_1, b_2\}$. Person a_1 prefers as partner Person b_2 , and Person a_2 prefers as partner Person b_1 . Reciprocally, Person b_1 prefers Person a_2 over a_1 and Person b_2 finally prefers a_1 over a_2 . There exist only two possible maximal matchings,

- (1) a_1 with b_1 and a_2 with b_2 , or
- (2) a_1 with b_2 and a_2 with b_1 .

Making the best matching decision in this setting here is trivial. Choosing matching (1) will result in an ordinal correlation index of -1 for all four persons, whereas matching (2) is in total ordinal concordance with everybody's preferences and will result in an average ordinal correlation index of +1.0.

Can we generalise this approach to larger groups and partially determined ordinal correlation scores?

Reciprocal linear voting profiles

Let us consider two groups of size $k = 5$. Individual pairing preferences of the persons in group A and group B may be randomly generated with *reciprocal RandomLinearVotingProfile* instances called $lvA1$ and $lvB1$ (see below).

```

1 >>> from votingProfiles import RandomLinearVotingProfile
2 >>> k = 5
3 >>> lvA1 = RandomLinearVotingProfile(
4 ...     number0fVoters=k, number0fCandidates=k,
5 ...     votersIdPrefix='a',
6 ...     candidatesIdPrefix='b', seed=1)
7 >>> lvA1.save('lvA1')
8 >>> lvB1 = RandomLinearVotingProfile(
9 ...     number0fVoters=k, number0fCandidates=k,
10 ...    votersIdPrefix='b',
11 ...    candidatesIdPrefix='a', seed=2)
12 >>> lvB1.save('lvB1')
```

We may inspect the resulting stored pairing preferences for each person in group A and each person in group B with the `showLinearBallots()` method⁴⁹.

```

1 >>> from votingProfiles import LinearVotingProfile
2 >>> lvA1 = LinearVotingProfile('lvA1')
3 >>> lvA1.showLinearBallots()
4
5 voters           marginal
6 (weight)        candidates rankings
7 a1(1):          ['b3', 'b4', 'b5', 'b1', 'b2']
8 a2(1):          ['b3', 'b5', 'b4', 'b2', 'b1']
9 a3(1):          ['b4', 'b2', 'b1', 'b3', 'b5']
10 a4(1):         ['b2', 'b4', 'b1', 'b5', 'b3']
```

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⁴⁹ The stored versions $lvAx.py$, $lvBx.py$, $apA1.py$ and $apB1.py$ of the examples of reciprocal random voting profiles discussed in the intergroup pairing tutorial may be found in the *examples* directory of the *Digraph3* resources.

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```

10    a5(1):      ['b4', 'b2', 'b3', 'b1', 'b5']
11 >>> lvB1 = LinearProfile('lvB1')
12 >>> lvB1.showLinearBallots()
13     voters      marginal
14   (weight)    candidates rankings
15   b1(1):      ['a3', 'a2', 'a4', 'a5', 'a1']
16   b2(1):      ['a5', 'a3', 'a1', 'a4', 'a2']
17   b3(1):      ['a3', 'a4', 'a1', 'a5', 'a2']
18   b4(1):      ['a3', 'a4', 'a1', 'a2', 'a5']
19   b5(1):      ['a3', 'a4', 'a1', 'a2', 'a5']

```

With these given individual pairing preferences, there does no more exist a quick trivial matching solution to our pairing problem. Persons a_1 and a_2 prefer indeed to be matched to the same Person b_3 . Worse, Persons b_1, b_3, b_4 and b_5 all four want also to be preferably matched to a same Person a_3 , but Person a_3 apparently prefers as partner only Person b_4 .

How to find now a maximal matching that will fairly balance the individual pairing preferences of both groups? To solve this decision problem, we first must generate the potential decision actions, i.e. all potential maximal matchings between group A and group B .

Generating the set of potential maximal matchings

The maximal matchings correspond in fact to the maximal independent sets of edges of the complete bipartite graph linking group A to group B . To compute this set we will use the `CompleteBipartiteGraph` class from the `graphs` module (see Lines 3-4 below).

```

1 >>> groupA = [p for p in lvA1.voters]
2 >>> groupB = [p for p in lvB1.voters]
3 >>> from graphs import CompleteBipartiteGraph
4 >>> bpg = CompleteBipartiteGraph(groupA,groupB)
5 >>> bpg
*----- Graph instance description -----
6 Instance class : Graph
7 Instance name  : bipartitegraph
8 Graph Order   : 10
9 Graph Size    : 25
10 Valuation domain : [-1.00; 1.00]
11 Attributes    : ['name', 'vertices',
12                   'verticesKeysA', 'verticesKeysB',
13                   'order', 'valuationDomain',
14                   'edges', 'size', 'gamma']

```

Now, the maximal matchings of the bipartite graph bpg correspond to the MISs of its line graph lpg . Therefore we use the `LineGraph` class from the `graphs` module.

```

1 >>> from graphs import LineGraph
2 >>> lbgp = LineGraph(bpg)
3 >>> lbgp
4     ----- Graph instance description -----
5     Instance class      : LineGraph
6     Instance name       : line-bipartite_completeGraph_graph
7     Graph Order         : 25
8     Graph Size          : 100
9 >>> lbgp.computeMIS()
10 >>> lbgp.showMIS()
11     ---- Maximal Independent Sets ---
12     number of solutions: 120
13     cardinality distribution
14     card.: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, ...]
15     freq.: [0, 0, 0, 0, 0, 120, 0, 0, 0, 0, 0, ...]
16     stability number : 5
17     execution time: 0.01483 sec.
18     Results in self.misset

```

The set of maximal matchings between persons of groups A and B has cardinality $factorial\ 5! = 120$ (see Line 15 above) and is stored in attribute $lbgp.misset$. We may for instance print the pairing corresponding to the first maximal matching.

```

1 >>> for m in lbgp.misset[0]:
2     ...     pair = list(m)
3     ...     pair.sort()
4     ...     print(pair)
5     ['a1', 'b4']
6     ['a2', 'b3']
7     ['a3', 'b5']
8     ['a4', 'b2']
9     ['a5', 'b1']

```

Each maximal matching delivers thus for each person a partially determined ranking. For Person a_1 , for instance, this matching ranks b_4 before all the other persons from group B and for Person b_4 , for instance, this matching ranks a_1 before all other persons from group A .

How to judge now the global pairing fitness of this matching?

Measuring the fitness of a matching from a personal perspective

Below we may reinspect the actual pairing preferences of each person.

```

1 >>> lvA1.showLinearBallots()
2     voters           marginal
3     (weight)    candidates rankings
4     a1(1):      ['b3', 'b4', 'b5', 'b1', 'b2']

```

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```

5      a2(1):      ['b3', 'b5', 'b4', 'b2', 'b1']
6      a3(1):      ['b4', 'b2', 'b1', 'b3', 'b5']
7      a4(1):      ['b2', 'b4', 'b1', 'b5', 'b3']
8      a5(1):      ['b4', 'b2', 'b3', 'b1', 'b5']
9 >>> lvB1.showLinearBallots()
10     voters           marginal
11     (weight)        candidates rankings
12     b1(1):          ['a3', 'a2', 'a4', 'a5', 'a1']
13     b2(1):          ['a5', 'a3', 'a1', 'a4', 'a2']
14     b3(1):          ['a3', 'a4', 'a1', 'a5', 'a2']
15     b4(1):          ['a3', 'a4', 'a1', 'a2', 'a5'] [highlighted]
16     b5(1):          ['a3', 'a4', 'a1', 'a2', 'a5']

```

In the first matching shown in the previous Listing, Person a_1 is for instance matched with Person b_4 , which was her second choice. Whereas for Person b_4 the match with Person a_1 is only her third choice.

For a given person, we may hence compute the ordinal correlation –the relative number of correctly ranked persons minus the relative number of incorrectly ranked persons– between the partial ranking defined by the given matching and the individual pairing preferences, just ignoring the indeterminate comparisons.

For Person a_1 , for instance, the matching ranks b_4 before all the other persons from group B whereas a_1 's individual preferences rank b_4 second behind b_3 . We observe hence 3 correctly ranked persons – b_5 , b_1 and b_2 – minus 1 incorrectly ranked person – b_3 – out of four determined comparisons. The resulting ordinal correlation index amounts to $(3-1)/4 = +0.5$.

For Person b_4 , similarly, we count 2 correctly ranked persons – a_2 and a_5 – and 2 incorrectly ranked persons – a_3 and a_4 – out of the four determined comparisons. The resulting ordinal correlation amounts hence to $(2-2)/4 = 0.0$

For a given maximal matching we obtain thus 10 ordinal correlation indexes, one for each person in both groups. And, we may now score the global fitness of a given matching by computing the average over all the individual ordinal correlation indexes observed in group A and group B .

Computing the fairest intergroup pairing

The `pairings` module provides the `FairestInterGroupPairing` class for solving, following this way, a given pairing problem of tiny order 5 (see below).

```

1 >>> from pairings import FairestInterGroupPairing
2 >>> fp = FairestInterGroupPairing(lvA1,lvB1)
3 >>> fp
4 *----- FairPairing instance description -----*
5   Instance class      : FairestInterGroupPairing
6   Instance name       : pairingProblem
7   Groups A and B size : 5

```

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```

8 Attributes          : ['name', 'order', 'vpA', 'vpB',
9                      'pairings', 'matching',
10                     'vertices', 'valuationDomain',
11                     'edges', 'gamma', 'runTimes']

```

The class takes as input two reciprocal `VotingProfile` objects describing the individual pairing preferences of the two groups A and B of persons. The class constructor delivers the attributes shown above. vpA and vpB contain the pairing preferences. The *pairings* attribute gathers all maximal matchings –the potential decision actions– ordered by decreasing average ordinal correlation with the individual pairing preferences, whereas the *matching* attribute delivers directly the first-ranked maximal matching –*pairings[0][0]*– and may be consulted as shown in the Listing below. The resulting *fp* object models in fact a `BipartiteGraph` object where the *vertices* correspond to the set of persons in both groups and the bipartite *edges* model the fairest maximal matching. The `showFairestPairing()` method prints out the fairest matching.

```

1 >>> fp.showFairestPairing(rank=1,
2 ...     WithIndividualCorrelations=True)
3 -----
4 Fairest pairing
5 ['a1', 'b3']
6 ['a2', 'b5']
7 ['a3', 'b1']
8 ['a4', 'b4']
9 ['a5', 'b2']
10 groupA correlations:
11   'a1': +1.000
12   'a2': +0.500
13   'a3':  0.000
14   'a4': +0.500
15   'a5': +0.500
16 group A average correlations (a) : 0.500
17 group A standard deviation       : 0.354
18 -----
19 groupB Correlations:
20   'b1': +1.000
21   'b2': +1.000
22   'b3':  0.000
23   'b4': +0.500
24   'b5': -0.500
25 group B average correlations (b) : 0.400
26 group B standard deviation       : 0.652
27 -----
28 Average correlation      : 0.450
29 Standard Deviation       : 0.497
30 Unfairness |(a) - (b)| : 0.100

```

Three persons $-a_1$, b_1 and b_2 – get as partner their first choice (+1.0). Four persons $-a_2$, a_4 , a_5 and b_4 – get their second choice (+0.5). Two persons $-a_3$ and b_3 – get their third choice (0.0). Person b_5 gets only her fourth choice. Both group get very similar average ordinal correlation results – +0.500 versus +0.400– resulting in a low unfairness score (see last Line above)

In this problem we may observe a 2nd-ranked pairing, of same average correlation score +0.450, but with both a larger standard deviation (0.55 versus 0.45) and a larger unfairness score (0.300 versus 0.100).

```

1  >>> fp.showFairestPairing(rank=2,
2      ...     WithIndividualCorrelations=True)
3  -----
4  2nd-ranked pairing
5  ['a1', 'b3']
6  ['a2', 'b5']
7  ['a3', 'b4']
8  ['a4', 'b1']
9  ['a5', 'b2']
10 group A correlations:
11 'a1': +1.000
12 'a2': +0.500
13 'a3': +1.000
14 'a4': +0.000
15 'a5': +0.500
16 group A average correlations (a) : 0.600
17 group A standard deviation       : 0.418
18 -----
19 group B correlations:
20 'b1': +0.000
21 'b2': +1.000
22 'b3': +0.000
23 'b4': +1.000
24 'b5': -0.500
25 group B average correlations (b) : 0.300
26 group B standard deviation       : 0.671
27 -----
28 Average correlation      : 0.450
29 Standard Deviation       : 0.550
30 Unfairness |(a) - (b)| : 0.300

```

In this second-fairest pairing solution, four persons $-a_1$, a_3 , b_2 and b_4 – get their first choice. Only two persons $-a_2$ and a_5 – get their second choice, but three persons $-a_4$, b_1 and b_3 – now only get their third choice. Person b_5 gets unchanged her fourth choice. Despite a same average correlation (+0.45), the distribution of the individual correlations appears less balanced than in the previous solution, as confirmed by the higher standard deviation. In the latter pairing, group A shows indeed an average correlation of $+3.000/5 = +0.600$, whereas group B obtains only an average correlation of $1.500/5 = +0.300$.

In the previous pairing, group A gets a lesser average correlation of $+0.500$. And, group B obtains here a higher average correlation of $2.000/5 = +0.400$. Which makes the first-ranked pairing with same average ordinal correlation yet lower standard deviation, an effectively fairer matching decision.

One may visualise a pairing result with the `exportPairingGraphViz()` method (see Fig. 2.29 below).

```
>>> fp.exportPairingGraphViz(fileName='fairPairing',
...                               matching=fp.matching)
dot -Tpng fairPairing.dot -o fairPairing.png
```

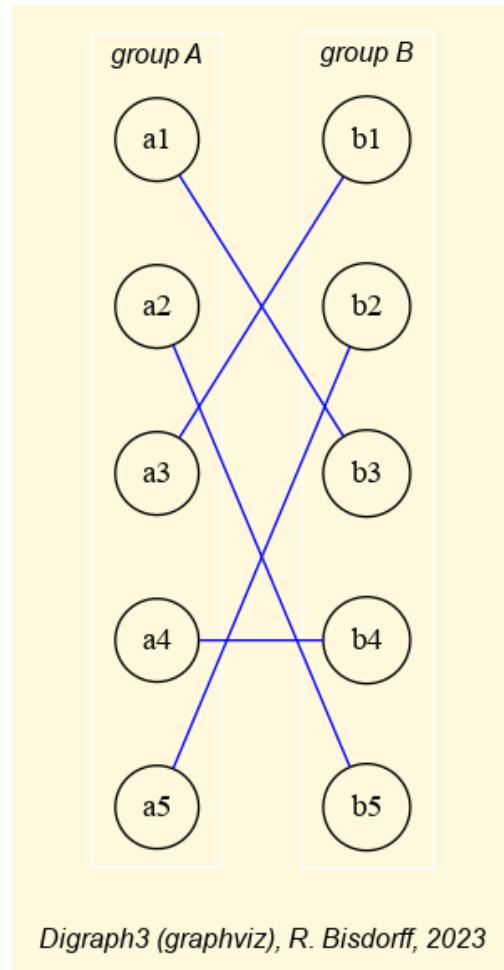


Fig. 2.29: Fairest intergroup pairing decision

A matching corresponds in fact to a certain permutation of the positional indexes of the persons in group B . We may compute this permutation and construct the corresponding permutation graph.

```
1 >>> permutation = fp.computePermutation(fp.matching)
2 >>> from graphs import PermutationGraph
3 >>> pg = PermutationGraph(permutation)
4 >>> pg
```

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```

5   *----- Graph instance description -----*
6   Instance class      : PermutationGraph
7   Instance name       : matching-permutation
8   Graph Order         : 5
9   Permutation          : [3, 5, 1, 4, 2]
10  Graph Size          : 6
11  Valuation domain   : [-1.00; 1.00]
12  Attributes          : ['name', 'vertices', 'order',
13                            'permutation', 'valuationDomain',
14                            'edges', 'size', 'gamma']
15  >>> pg.exportPermutationGraphViz(fileName='fairPairingPermutation')
16  *---- exporting a dot file for GraphViz tools -----*
17  Exporting to fairPairingPermutation.dot
18  neato -n -Tpng fairPairingPermutation.dot -o fairPairingPermutation.png

```

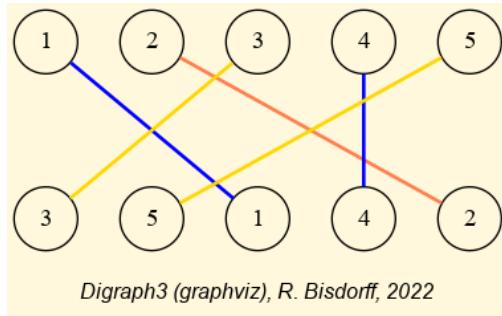


Fig. 2.30: Fairest pairing's coloured matching diagram

In Fig. 2.30 is shown the coloured matching diagram of the index permutation [3, 5, 1, 4, 2] modelled by the fairest pairing decision.

Mind that our `FairestInterGroupPairing` class does not provide an efficient algorithm for computing fair pairings; far from it. Our class constructor's complexity is in $O(k!)$, which makes the class totally unfit for solving any real pairing problem even of small size. The class has solely the didactic purpose of giving a first insight into this important and practically relevant decision problem. For efficiently solving this kind of pairing decision problems it is usual professional practice to concentrate the set of potential pairing decisions on *stable* matchings⁴⁵.

Fair versus stable pairings

In classical economics, where the homo economicus is supposed to ignore any idea of fairness and behave solely in exact accordance with his rational self-interest, a pairing is only considered suitable when there appear no matching *instabilities*. A matching is indeed called *stable* when there does not exist in the matching a couple of pairs such that it may be interesting for both a paired person from group *A* and a paired person from group *B* to abandon their given partners and form together a new pair. Let us consider for instance the following situation,

⁴⁵ See https://en.wikipedia.org/wiki/Gale%20%20Shapley_algorithm

Person $a3$ is paired with Person $b1$.

Person $b4$ is paired with Person $a4$.

Person $a3$ would rather be with Person $b4$

Person $b4$ would rather be with Person $a3$

Computing such a *stable* matching may be done with the famous *Gale-Shapley* algorithm (⁴³ Page 149, ⁴⁵), available via the `FairestGaleShapleyMatching` class (see below Line 1).

```
1 >>> from pairings import FairestGaleShapleyMatching
2 >>> fgs = FairestGaleShapleyMatching(lvA1,lvB1)
3 >>> fgs.showPairing(fgs.matching)
4 -----
5     Pairing
6     ['a1', 'b3']
7     ['a2', 'b5']
8     ['a3', 'b4']
9     ['a4', 'b1']
10    ['a5', 'b2']
```

We have already seen this *Gale-Shapley* pairing solution. It is in fact the 2nd-ranked fairest pairing, discussed in the previous section. Now, is the fact of being *stable* any essential characteristic of a fair pairing solution?

In a Monte Carlo simulation of solving 1000 random pairing problems of order 5, we obtain the following distribution of the actual fairness ranking indexes of the fairest stable matching.

⁴³ [GAL-1962]

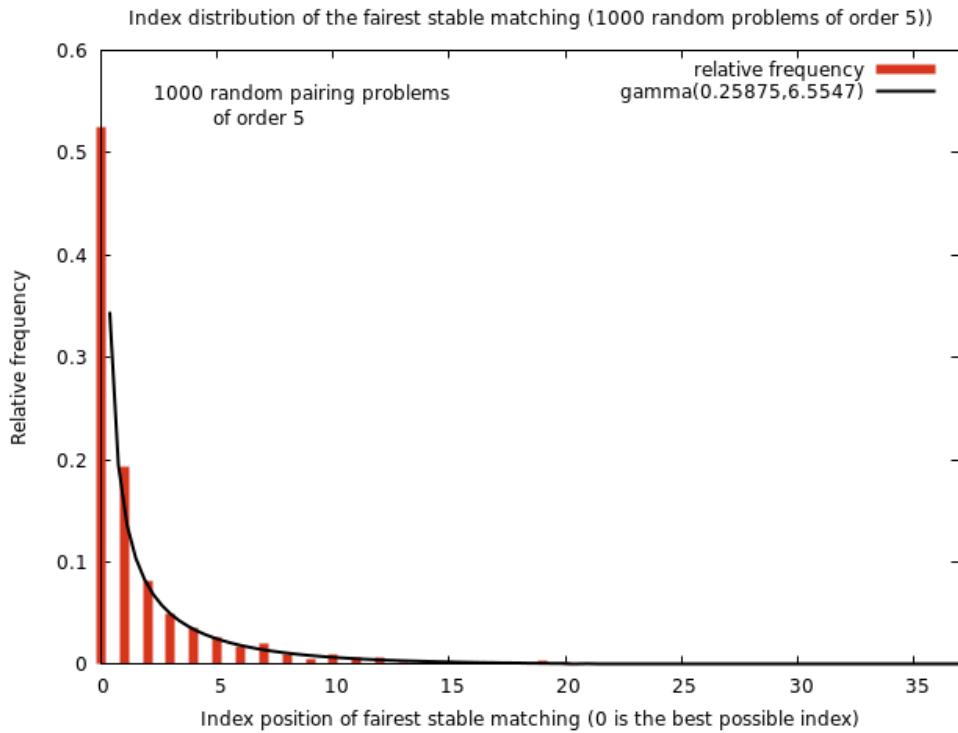


Fig. 2.31: Distribution of the fairness rank of the fairest stable matching

In Fig. 2.31 we may notice that only in a bit more than 50% of the cases, the overall fairest matching –of index 0 in the `fp.pairings` list– is indeed stable.

And the overall fairest matching in our example above is, for instance, *not* a stable matching (see Lines 2-3 below).

```

1 >>> fp.isStableMatching(fp.matching,Comments=True)
2 -----
3 ['a1', 'b3']
4 ['a2', 'b5']
5 ['a3', 'b1']
6 ['a4', 'b4']
7 ['a5', 'b2']
8     is unstable!
9 a3 b4 <- b1: rank improvement 0 --> 2
10 b4 a3 <- a4: rank improvement 0 --> 1

```

If we resolve its unstable pairs $[\text{a}3, \text{b}1] \rightarrow [\text{a}3, \text{b}4]$, and $[\text{a}4, \text{b}4] \rightarrow [\text{a}4, \text{b}1]$ – we recover the previous *Gale-Shapley* solution, i.e the 2nd-fairest pairing solution (see above).

Unfairness of the Gale-Shapley solution

The *Gale-Shapley* algorithm is actually based on an asymmetrical handling of the two groups of persons by distinguishing a matches proposing group. In our implementation here⁴⁴, it is group *A*. Now, the proposing group gets by the *Gale-Shapley* algorithm the

⁴⁴ Our implementation is based on John Lekberg's blog. See <https://johnlekgberg.com/blog/2020-08-22-stable-matching.html>

best possible average group correlation, but of costs of the non-proposing group who gets the worst possible average group correlation in any stable matching^{Page 149, 45}. We may check as follows this unfair result on the previous *Gale-Shapley* solution.

```

1  >>> fgs.showMatchingFairness(fgs.matching,
2      ...      WithIndividualCorrelations=True)
3  -----
4  ['a1', 'b3']
5  ['a2', 'b5']
6  ['a3', 'b4']
7  ['a4', 'b1']
8  ['a5', 'b2']
9  -----
10 group A correlations:
11   'a1': +1.000
12   'a2': +0.500
13   'a3': +1.000
14   'a4': +0.000
15   'a5': +0.500
16 group A average correlations (a) : 0.600
17 group A standard deviation       : 0.418
18 -----
19 group B correlations:
20   'b1': +0.000
21   'b2': +1.000
22   'b3': +0.000
23   'b4': +1.000
24   'b5': -0.500
25 group B average correlations (b) : 0.300
26 group B standard deviation       : 0.671
27 -----
28 Average correlation      : 0.450
29 Standard Deviation       : 0.550
30 Unfairness |(a) - (b)| : 0.300

```

Four persons out of five from group *A* are matched to their first or second choices. When reversing the order of the given linear voting profiles *lvA1* and *lvB1*, we obtain a second *Gale-Shapley* solution *gs2* favouring this time the persons in group *B*.

```

1  >>> gs2 = fgs.computeGaleShapleyMatching(Reverse=True)
2  >>> fgs.showMatchingFairness(gs2,
3      ...      WithIndividualCorrelations=True)
4  -----
5  ['a1', 'b3']
6  ['a2', 'b1']
7  ['a3', 'b4']
8  ['a4', 'b5']
9  ['a5', 'b2']

```

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```
10 -----
11 group A correlations:
12   'a1': +1.000
13   'a2': -1.000
14   'a3': +1.000
15   'a4': -0.500
16   'a5': +0.500
17 group A average correlations (a) : 0.200
18 group A standard deviation      : 0.908
19 -----
20 group B correlations:
21   'b1': +0.500
22   'b2': +1.000
23   'b3': +0.000
24   'b4': +1.000
25   'b5': +0.500
26 group B average correlations (b) : 0.600
27 group B standard deviation      : 0.418
28 -----
29 Average correlation      : 0.400
30 Standard Deviation       : 0.699
31 Unfairness |(a) - (b)| : 0.400
```

In this reversed *Gale-Shapley* pairing solution, it is indeed the group *B* that appears now better served. Yet, it is necessary to notice now, besides the even more unbalanced group average correlations, the lower global average correlation (+0.400 compared to +0.450) coupled with both an even higher standard deviation (0.699 compared to 0.550) and a higher unfairness score (0.400 versus 0.300).

It may however also happen that both *Gale-Shapley* matchings, as well as the overall fairest one, are a same unique fairest pairing solution. This is for instance the case when considering the following example of reciprocal *lvA2* and *lvB2* profiles^{Page 142, 49}.

```
1 >>> lvA2 = LinearVotingProfiles('lvA2')
2 >>> lvA2.showLinearBallots()
3 voters           marginal
4 (weight)        candidates rankings
5 a1(1):          ['b1', 'b5', 'b2', 'b4', 'b3']
6 a2(1):          ['b4', 'b3', 'b5', 'b2', 'b1']
7 a3(1):          ['b3', 'b5', 'b1', 'b2', 'b4']
8 a4(1):          ['b4', 'b2', 'b5', 'b3', 'b1']
9 a5(1):          ['b5', 'b2', 'b3', 'b4', 'b1']
10 # voters: 5
11 >>> lvB2 = LinearVotingProfile('lvB2')
12 >>> lvB2.showLinearBallots()
13 voters           marginal
14 (weight)        candidates rankings
```

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```

15 b1(1):      ['a1', 'a2', 'a5', 'a3', 'a4']
16 b2(1):      ['a2', 'a5', 'a3', 'a4', 'a1']
17 b3(1):      ['a3', 'a4', 'a1', 'a5', 'a2']
18 b4(1):      ['a4', 'a1', 'a2', 'a3', 'a5']
19 b5(1):      ['a2', 'a1', 'a5', 'a3', 'a4']
20 # voters: 5
21 >>> fp = FairestInterGroupPairing(lvA2,lvB2,StableMatchings=True)
22 >>> fp.showMatchingFairness()
23 *-----*
24 ['a1', 'b1']
25 ['a2', 'b5']
26 ['a3', 'b3']
27 ['a4', 'b4']
28 ['a5', 'b2']
29 group A average correlations (a) : 0.700
30 group A standard deviation       : 0.447
31 group B average correlations (b) : 0.900
32 group B standard deviation       : 0.224
33 Average correlation       : 0.800
34 Standard Deviation        : 0.350
35 Unfairness |(a) - (b)| : 0.200
36 >>> print('Index of stable matchings:'. fp.stableIndex)
37 Index of stable matchings: [0]

```

In this case, the individual pairing preferences lead easily to the overall fairest pairing (see above). Indeed, three couples out of 5, namely $[a_1, b_1]$, $[a_3, b_3]$ and $[a_4, b_4]$, do share their mutual first choices. For the remaining couples – $[a_2, b_5]$ and $[a_5, b_2]$ – the fairest matching gives them their third and first, respectively their first and second choice. Furthermore, there exists only one stable matching and it is actually the overall fairest one. When setting the *StableMatchings* flag of the *FairestInterGroupPairing* class to *True*, we get the *stableIndex* list with the actual index numbers of all stable maximal matchings (see Lines 19 and 34-35).

But the contrary may also happen. Below we show individual pairing preferences – stored in files *lvA3.py* and *lvB3.py* – for which the *Gale-Shapley* algorithm is not delivering a satisfactory pairing solution^{Page 142, 49}.

```

1 >>> from votingProfiles import LinearVotingProfile
2 >>> lvA3 = LinearVotingProfile('lvA3')
3 >>> lvA3.showLinearBallots()
4 voters           marginal
5 (weight)    candidates rankings
6 a1(1):      ['b5', 'b6', 'b4', 'b3', 'b1', 'b2']
7 a2(1):      ['b6', 'b1', 'b4', 'b5', 'b3', 'b2']
8 a3(1):      ['b6', 'b3', 'b4', 'b1', 'b5', 'b2']
9 a4(1):      ['b3', 'b4', 'b2', 'b6', 'b5', 'b1']
10 a5(1):     ['b3', 'b4', 'b5', 'b1', 'b6', 'b2']

```

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```

11 a6(1):  ['b3', 'b5', 'b1', 'b6', 'b4', 'b2']
12   # voters: 6
13 >>> lvB3 = LinearVotingProfile('lvB3')
14 >>> lvB3.showLinearBallots()
15 voters           marginal
16 (weight)    candidates rankings
17 b1(1):  ['a3', 'a4', 'a6', 'a1', 'a5', 'a2']
18 b2(1):  ['a6', 'a4', 'a1', 'a3', 'a5', 'a2']
19 b3(1):  ['a3', 'a2', 'a4', 'a1', 'a6', 'a5']  

20 b4(1):  ['a4', 'a2', 'a5', 'a6', 'a1', 'a3']
21 b5(1):  ['a4', 'a2', 'a3', 'a6', 'a1', 'a5']
22 b6(1):  ['a4', 'a3', 'a1', 'a5', 'a6', 'a2']
23   # voters: 6

```

The individual pairing preferences are very contradictory. For instance, Person's a_2 first choice is b_6 whereas Person b_6 dislikes Person a_2 most. Similar situation is given with Persons a_5 and b_3 .

In this pairing problem there does exist only one matching which is actually stable and it is a very unfair pairing. Its fairness index is 140 (see Line 3-4 below).

```

1 >>> fp = FairestInterGroupPairing(lvA3,lvB3,
2 ...                               StableMatchings=True)
3 >>> fp.stableIndex
4 [140]
5 >>> g1 = fp.computeGaleShapleyMatching()
6 >>> fp.showMatchingFairness(g1,
7 ...                               WithIndividualCorrelations=True)
8 *-----*
9  ['a1', 'b1']
10 ['a2', 'b4']
11 ['a3', 'b6']
12 ['a4', 'b3']
13 ['a5', 'b2']
14 ['a6', 'b5']
15 -----
16 group A correlations:
17 'a1': -0.600
18 'a2': +0.200
19 'a3': +1.000
20 'a4': +1.000
21 'a5': -1.000
22 'a6': +0.600
23 group A average correlation (a) : 0.200
24 group A standard deviation      : 0.839
25 -----
26 group B correlations:

```

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```
27 'b1': -0.200
28 'b2': -0.600
29 'b3': +0.200
30 'b4': +0.600
31 'b5': -0.200
32 'b6': +0.600
33 group B average correlation (b) : 0.067
34 group B standard deviation      : 0.484
35 -----
36 Average correlation      : 0.133
37 Standard Deviation       : 0.657
38 Unfairness |(a) - (b)| : 0.133
```

Indeed, both group correlations are very weak and show furthermore high standard deviations. Five out of the twelve persons obtain a negative correlation with their respective pairing preferences. Only two persons from group *A* –*a3* and *a4*– get their first choice, whereas Person *a5* is matched with her least preferred partner (see Lines 19-21). In group *B*, no apparent attention is put on choosing interesting partners (see Lines 27-32).

The fairest matching looks definitely more convincing.

```
1 >>> fp.showMatchingFairness(fp.matching,
2 ...     WithIndividualCorrelations=True)
3 -----
4 ['a1', 'b6']
5 ['a2', 'b5']
6 ['a3', 'b3']
7 ['a4', 'b2']
8 ['a5', 'b4']
9 ['a6', 'b1']
10 -----
11 group A correlations:
12 'a1': +0.600
13 'a2': -0.200
14 'a3': +0.600
15 'a4': +0.200
16 'a5': +0.600
17 'a6': +0.200
18 group A average correlation (a) : 0.333
19 group A standard deviation      : 0.327
20 -----
21 group B correlations:
22 'b1': +0.200
23 'b2': +0.600
24 'b3': +1.000
25 'b4': +0.200
26 'b5': +0.600
```

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```

27 'b6': +0.200
28 group B average correlation (b) : 0.467
29 group B standard deviation      : 0.327
30 -----
31 Average correlation      : 0.400
32 Standard Deviation       : 0.319
33 Unfairness |(a) - (b)| : 0.133

```

Despite the very contradictory individual pairing preferences and a same unfairness score, only one person, namely $a2$, obtains here a choice in negative correlation with her preferences (see Line 13). The group correlations and standard deviations are furthermore very similar (lines 18 and 28).

The fairest solution is however far from being stable. With three couples of pairs that are potentially unstable, the first and stable unique *Gale-Shapley* matching is with its fairness index 140 indeed far behind many fairer pairing solutions (see below).

```

1 >>> fp.isStableMatching(fp.matching,Comments=True)
2 Unstable match: Pair(groupA='a4', groupB='b2')
3                 Pair(groupA='a5', groupB='b4')
4 a4 b2 <-- b4
5 b4 a5 <-- a4
6 Unstable match: Pair(groupA='a2', groupB='b5')
7                 Pair(groupA='a5', groupB='b4')
8 a2 b5 <-- b4
9 b4 a5 <-- a2
10 Unstable match: Pair(groupA='a3', groupB='b3')
11                 Pair(groupA='a1', groupB='b6')
12 a3 b3 <-- b6
13 b6 a1 <-- a3

```

How likely is it to obtain such an unfair *Gale-Shapley* matching? With our Monte Carlo simulation of 1000 random pairing problems of order 5, we may empirically check the likely fairness index of the fairest of both *Gale-Shapley* solutions.

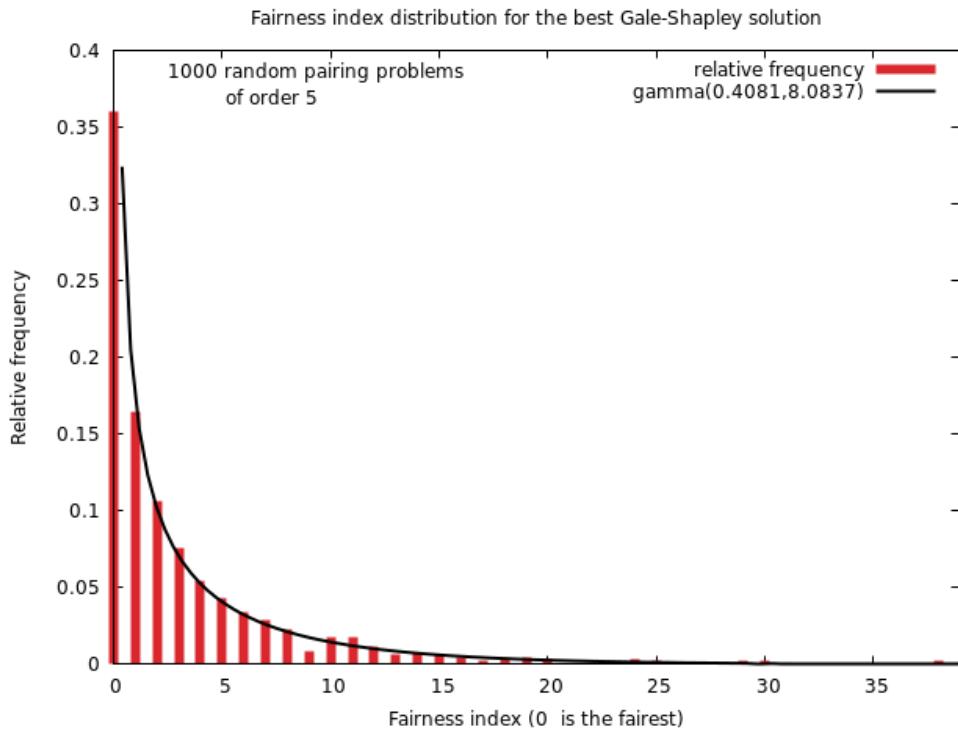


Fig. 2.32: Distribution of the fairness index of the fairest *Gale-Shapley* matching

In Fig. 2.32, we see that the fairest of both *Gale-Shapley* solutions will correspond to the overall fairest pairing (index = 0) in about 36% out of the 1000 random cases. Yet, it is indeed the complexity in $O(k^2)$ of the *Gale-Shapley* algorithm that makes it an interesting alternative to our brute force approach in complexity $O(k!)$.

It is worthwhile noticing furthermore that the number of stable matchings is in general very small compared to the size of the huge set of potential maximal matchings as shown in Fig. 2.33.

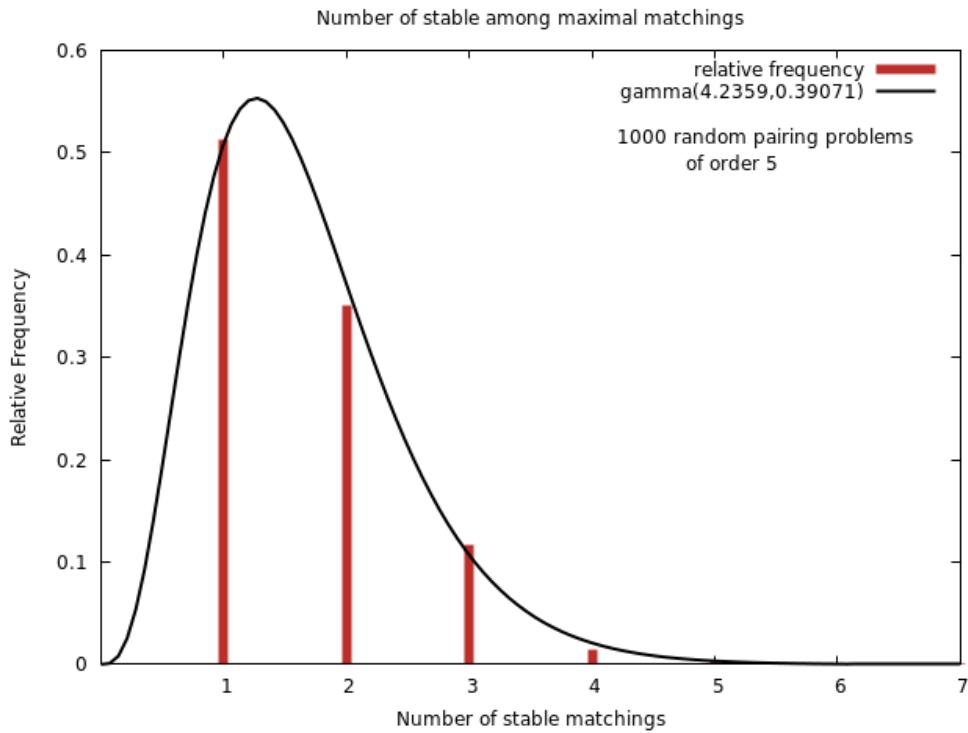


Fig. 2.33: Distribution of the number of stable matchings

In the simulation of 1000 random pairing problems of order 5, we observe indeed never more than seven stable matchings and the expected number of stable matchings is between one and two out of 120. It could therefore be opportune to limit our potential set of maximal matchings –the decisions actions– to solely stable matchings, as is currently the usual professional solving approach in pairing problems of this kind. Even if we would very likely miss the overall fairest pairing solution.

Dropping the stability requirement

Dropping however the *stability* requirement opens a second way of reducing the actual complexity of the fair pairing problem. This way goes by trying to enhance the fairness of a *Gale-Shapley* matching via a *hill-climbing* heuristic where we swap partners in couples of pairs that mostly increase the average ordinal correlation and decrease the gap between the groups' correlations.

With this strategy we may hence expect to likely reach one of the fairest possible matching solutions. In a Monte Carlo simulation of 1000 random pairing problems of order 6 we may indeed notice in Fig. 2.34 that we reach in a very limited number of swaps –less than $2 \times k$ – a fairness index less than [3] in nearly 95% of the cases. The weakest fairness index found is 16.

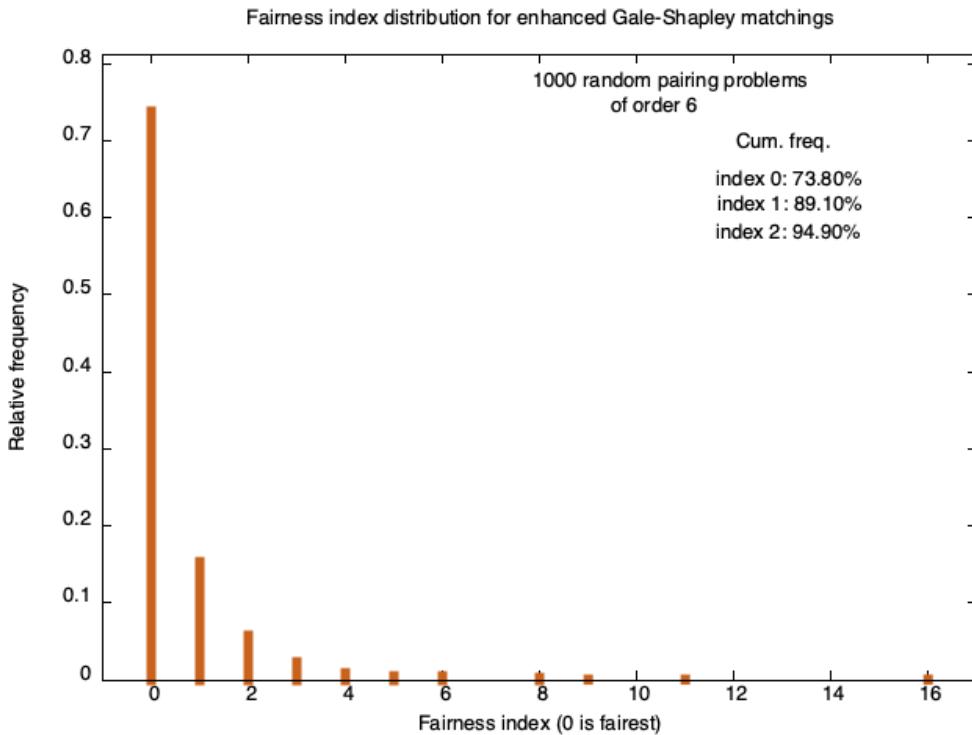


Fig. 2.34: Distribution of the fairness index of enhanced Gale-Shapley solutions

In the following example of a pairing problem of order 6, we observe only one unique stable matching with fairness index [12], in fact a very unfair *Gale-Shapley* matching completely ignoring the individual pairing preferences of the persons in group B (see Line 15 below).

```

1 >>> gs = FairestGaleShapleyMatching(lvA,lvB,
2 ...                               Comments=True)
3 Fairest Gale-Shapley matching
4 -----
5 ['a1', 'b3']
6 ['a2', 'b5']
7 ['a3', 'b4']
8 ['a4', 'b1']
9 ['a5', 'b6']
10 ['a6', 'b2']
11 -----
12 group A average correlation (a) : 0.867
13 group A standard deviation      : 0.327
14 -----
15 group B average correlation (b) : 0.000
16 group B standard deviation      : 0.704
17 -----
18 Average correlation      : 0.433
19 Standard Deviation       : 0.692
20 Unfairness |(a) - (b)| : 0.867

```

Taking this *Gale-Shapley* solution –`gs.matching`– as initial starting point, we try to swap partners in couple of pairs in order to improve the average ordinal correlation with all the individual pairing preferences and to reduce the gap between both groups. The `pairings` module provides the `FairnessEnhancedInterGroupMatching` class for this purpose.

```

1  >>> from pairings import \
2      FairnessEnhancedInterGroupMatching
3  >>> egs = FairnessEnhancedInterGroupMatching(
4      ...           lvA,lvB,initialMatching=gs.matching)
5  >>> egs.iterations
6  4
7  >>> egs.showMatchingFairness(egs.matching)
8  Fairness enhanced matching
9  -----
10 ['a1', 'b3']
11 ['a2', 'b2']
12 ['a3', 'b4']
13 ['a4', 'b6']
14 ['a5', 'b5']
15 ['a6', 'b1']
16 -----
17 group A average correlation (a) : 0.533
18 group A standard deviation     : 0.468
19 -----
20 group B average correlation (b) : 0.533
21 group B standard deviation     : 0.641
22 -----
23 Average correlation          : 0.533
24 Standard Deviation          : 0.535
25 Unfairness |(a) - (b)| : 0.000
26 >>> fp = FairestInterGroupPairing(lvA,lvB)
27 >>> fp.computeMatchingFairnessIndex(egs.matching)
28 0

```

With a slightly enhanced overall correlation (+0.533 versus +0.433), both groups obtain after four swapping iterations the same group correlation of +0.533 (Unfairness score = 0.0, see Lines 17, 20 and 25 above). And, furthermore, the fairness enhancing procedure attains the fairest possible pairing solution (see last Line).

Our *hill-climbing* fairness enhancing algorithm seems hence to be quite efficient. Considering that its complexity is about $O(k^3)$, we are effectively able to solve pairing problems of realistic orders.

Do we really need to start the fairness enhancing strategy from a previously computed *Gale-Shapley* solution? No, we may start from any initial matching. This opens the way for taking into account more realistic versions of the individual pairing preferences than complete reciprocal linear voting profiles.

Relaxing the requirement for complete linear voting profiles

Partial individual pairing preferences

In the classical approach to the pairing decision problem, it is indeed required that each person communicates a complete linearly ordered list of the potential partners. It seems more adequate to ask for only partially ordered lists of potential partners. With the *PartialLinearBallots* flag and the *lengthProbability* parameter the *RandomLinearVotingProfile* class provides a random generator for such a kind of individual pairing preferences (see Lines 5-6 below).

```
1 >>> from votingProfiles import RandomLinearVotingProfile
2 >>> vpA = RandomLinearVotingProfile(
3 ...     numberOfVoters=7,numberOfCandidates=7,
4 ...     votersIdPrefix='a',candidatesIdPrefix='b',
5 ...     PartialLinearBallots=True,
6 ...     lengthProbability=0.5,
7 ...     seed=1)
8 >>> vpA.showLinearBallots()
9     voters           marginal
10    (weight)      candidates rankings
11    a1(1):        ['b4', 'b7', 'b6', 'b3', 'b1']
12    a2(1):        ['b7', 'b5', 'b2', 'b6']
13    a3(1):        ['b1']
14    a4(1):        ['b2', 'b3', 'b5']
15    a5(1):        ['b2', 'b1', 'b4']
16    a6(1):        ['b6', 'b7', 'b2', 'b3']
17    a7(1):        ['b7', 'b6', 'b1', 'b3', 'b5']
18 # voters: 7
```

With length probability of 0.5, we obtain here for the seven persons in group *A* the partial lists shown above. Person *a3*, for instance, only likes to be paired with Person *b1*, whereas Person *a4* indicates three preferred partners in decreasing order of preference (see Lines 13-14 above).

We may generate similar reciprocal partial linear voting profiles for the seven persons in group *B*.

```
1 >>> vpB = RandomLinearVotingProfile(
2 ...     numberOfVoters=7,numberOfCandidates=7,
3 ...     votersIdPrefix='b',
4 ...     candidatesIdPrefix='a',
5 ...     PartialLinearBallots=True,
6 ...     lengthProbability=0.5,
7 ...     seed=2)
8 >>> vpB.showLinearBallots()
9     voters           marginal
10    (weight)      candidates rankings
11    b1(1):        ['a3', 'a4']
```

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```
12 b2(1):      ['a3', 'a4']
13 b3(1):      ['a2', 'a6', 'a3', 'a1']
14 b4(1):      ['a2', 'a6', 'a4']
15 b5(1):      ['a2', 'a1', 'a5']
16 b6(1):      ['a2', 'a7']
17 b7(1):      ['a7', 'a2', 'a1', 'a4']
18 # voters: 7
```

This time, Persons b_1 and b_2 indicate only two preferred pairing partners, namely both times Person a_3 before Person a_4 (see Lines 11-12 above).

Yet, it may be even more effective to only ask for reciprocal **approvals** and **disapprovals** of potential pairing partners.

Reciprocal bipolar approval voting profiles

Such random *bipolar approval* voting profiles may be generated with the `RandomBipolarApprovalVotingProfile` class (see below).

```
1 >>> from votingProfiles import \
2 ...     RandomBipolarApprovalVotingProfile
3 >>> k = 5
4 >>> apA1 = RandomBipolarApprovalVotingProfile(
5 ...         number_of_voters=k,
6 ...         number_of_candidates=k,
7 ...         voters_id_prefix='a',
8 ...         candidates_id_prefix='b',
9 ...         approval_probability=0.5,
10 ...        disapproval_probability=0.5,
11 ...        seed=None)
12 >>> apA1.save('apA1')
13 >>> apA1.show_bipolar_approvals()
14 Bipolar approval ballots
15 -----
16 a1 :
17 Approvals : ['b1', 'b5']
18 Disapprovals: ['b2']
19 a2 :
20 Approvals : ['b2']
21 Disapprovals: ['b1', 'b3', 'b4']
22 a3 :
23 Approvals : []
24 Disapprovals: ['b3', 'b5']
25 a4 :
26 Approvals : ['b1', 'b5']
27 Disapprovals: ['b2', 'b3', 'b4']
28 a5 :
29 Approvals : ['b2', 'b3']
```

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```
30 Disapprovals: ['b1', 'b5']  
31 Bipolar approval ballots
```

The *approvalProbability* and *disapprovalProbability* parameters determine the expected number of approved, respectively disapproved, potential pairing partners (see Lines 9-10). Person *a1*, for instance, approves two persons –*b1* and *b5*– and disapproves only Person *b2* (see Lines 17-18). Whereas Person *a3* does not approve anybody from group *B*, yet, disapproves *b3* and *b5*.

We may generate a similar random reciprocal bipolar approval voting profile for the persons in group *B*.

```
1 >>> apB1 = RandomBipolarApprovalVotingProfile(  
2 ...     numberOfVoters=k,  
3 ...     numberOfCandidates=k,  
4 ...     votersIdPrefix='b',  
5 ...     candidatesIdPrefix='a',  
6 ...     approvalProbability=0.5,  
7 ...     disapprovalProbability=0.5,  
8 ...     seed=None)  
9 >>> apB1.save('apB1')  
10 >>> apB1.showBipolarApprovals()  
11 Bipolar approval ballots  
12 -----  
13 b1 :  
14 Approvals : ['a2', 'a3']  
15 Disapprovals: ['a1', 'a4', 'a5']  
16 b2 :  
17 Approvals : ['a1', 'a2']  
18 Disapprovals: ['a4']  
19 b3 :  
20 Approvals : ['a5']  
21 Disapprovals: ['a2', 'a3']  
22 b4 :  
23 Approvals : ['a2']  
24 Disapprovals: ['a3', 'a5']  
25 b5 :  
26 Approvals : ['a4']  
27 Disapprovals: ['a1']
```

This time, Person *b1* approves two persons –*a2* and *a3*– and disapproves three persons –*a1*, *a4*, and *a5*– (see Lines 14-15 above).

Using Copeland scores for guiding the fairness enhancement

The partial linear voting profiles as well as the bipolar approval profiles determine for each person in both groups only a partial order on their potential pairing partners. In order to enhance the fairness of any given maximal matching, we must therefore replace the rank information of the complete linear voting profiles, as used in the *Gale-Shapley* algorithm, with the *Copeland* ranking scores obtained from the partial pairwise comparisons of potential partners. For this purpose we reuse again the `FairnessEnhancedInterGroupMatching` class , but without providing any initial matching (see below [Page 142, 49](#)).

```
1  >>> from pairings import \
2      ...     FairnessEnhancedInterGroupMatching
3  >>> from votingProfiles import BipolarApprovalVotingProfile
4  >>> apA1 = BipolarApprovalVotingProfile('apA1')
5  >>> apB1 = BipolarApprovalVotingProfile('apB1')
6  >>> fem = FairnessEnhancedInterGroupMatching(
7      ...         apA1, apB1, initialMatching=None,
8      ...         maxIterations=2*k,
9      ...         Comments=False)
10 >>> fem
11 *----- InterGroupPairing instance description -----*
12 Instance class      : FairnessEnhancedInterGroupMatching
13 Instance name       : fairness-enhanced-matching
14 Group sizes         : 5
15 Graph Order         : 10
16 Graph size          : 5
17 Partners swappings : 5
18 Attributes          : ['runTimes', 'vpA', 'vpB',
19                         'verticesKeysA', 'verticesKeysB', 'name',
20                         'order', 'maxIterations', 'copelandScores',
21                         'initialMatching', 'matching', 'iterations', 'history',
22                         'maxCorr', 'stDev', 'groupAScores', 'groupBScores',
23                         'vertices', 'valuationDomain', 'edges', 'size', 'gamma']
```

When no initial matching is given –*initialMatching* = *None*, which is the default setting– two initial matchings –the left matching (a_i, b_i) and the right matching (a_i, b_{-i}) for $i = 1, \dots, k$ – are used for starting the fairness enhancing procedure (see Line 7). The best solution of both is eventually retained. When the *initialMatching* parameter is set to ‘random’, a random shuffling –with given seed– of the persons in group *B* preceeds the construction of the right and left initial matchings. By default, the computation is limited to $2 \times k$ swappings of partners in order to master the potential occurrence of cycling situations. This limit may be adjusted if necessary with the *maxIterations* parameter (see Line 8). Such cycling swappings are furthermore controlled by the *history* attribute (see Line 21). The fairness enhanced *fem.matching* solution determines in fact a `BipartiteGraph` object (see last Line 23).

The actual pairing result obtained with the given bipolar approval ballots above is shown with the `showMatchingFairness()` method (see the Listing below). The *WithIndividu-*

alCorrelations flag allows to print out the individual pairing preference correlations for all persons in both groups (see Line 2).

```

1 >>> fem.showMatchingFairness(
2 ...             WithIndividualCorrelations=True)
3 -----
4 ['a1', 'b4']
5 ['a2', 'b2']
6 ['a3', 'b1']
7 ['a4', 'b5']
8 ['a5', 'b3']
9 -----
10 group A correlations:
11 'a1': -0.333
12 'a2': +1.000
13 'a3': +1.000
14 'a4': +1.000
15 'a5': +1.000
16 group A average correlation (a) : 0.733
17 group A standard deviation       : 0.596
18 -----
19 group B correlations:
20 'b1': +1.000
21 'b2': +1.000
22 'b3': +1.000
23 'b4': +0.333
24 'b5': +1.000
25 group B average correlation (b) : 0.867
26 group B standard deviation       : 0.298
27 -----
28 Average correlation      : 0.800
29 Standard Deviation       : 0.450
30 Unfairness |(a) - (b)| : 0.133

```

In group *A* and group *B*, all persons except *a1* and *b4* get an approved partner (see Lines 11 and 23). Yet, Persons *a1* and *b4* do not actually disapprove their respective match. Hence, the resulting overall ordinal correlation is very high (+0.800, see Line 28) and both groups show quite similar marginal correlation values (+0.733 versus +0.867, see Lines 16 and 25). The fairness enhanced matching we obtain in this case corresponds actually to the very fairest among all potential maximal matchings (see Lines 2-3 below).

```

1 >>> from pairings import FairestInterGroupPairing
2 >>> fp = FairestInterGroupPairing(apA1,apB1)
3 >>> fp.computeMatchingFairnessIndex(fem.matching)
4 0

```

Mind however that our fairness enhancing algorithm does not guarantee to end always in the very fairest potential maximal matching. In Fig. 2.35 is shown the result of a Monte Carlo simulation of 1000 random intergroup pairing problems of order 6 envolving

bipolar approval voting profiles with approval, resp. disapproval probabilities of 50%, resp. 20%. The failure rate to obtain the fairest pairing solution amounts to 12.4% with an average failure –optimal minus fairness enhanced average ordinal correlation– of -0.056 and a maximum failure of -0.292.

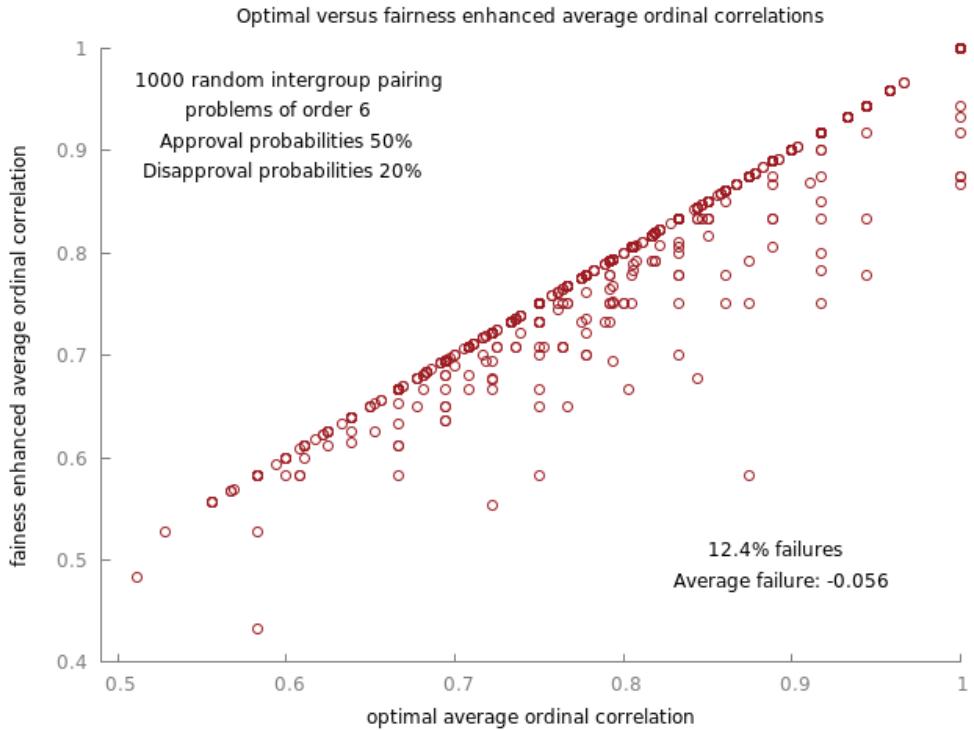


Fig. 2.35: Optimal versus fairness enhanced ordinal correlations

The proportion of failures depends evidently on the difficulty and the order of the pairing problem. We may however enhance the success rate of the fairness enhancing heuristic by choosing, like a Gale-Shapley stable in the case of linear voting profiles, a best determined *Copeland* ranking scores based initial matching.

Starting the fairness enhancement from a best determined Copeland matching

The partner swapping strategy relies on the *Copeland* ranking scores of a potential pairing candidate for all persons in both groups. These scores are precomputed and stored in the *copelandScores* attribute of the *FairnessEnhancedInterGroupMatching* object. When we add, for a pair $\{ai, bj\}$ both the *Copeland* ranking score of partner bj from the perspective of Person ai to the corresponding *Copeland* ranking score of partner ai from the perspective of Person bj to two times the observed minimal *Copeland* ranking score, we obtain a weakly determined complete bipartite graph object.

```

1 >>> from pairings import BestCopelandInterGroupMatching
2 >>> bcop = BestCopelandInterGroupMatching(apA1, apB1)
3 >>> bcop.showEdgesCharacteristicValues()
4     |   'b1'    'b2'    'b3'    'b4'    'b5'
5     |-----|-----|-----|-----|-----|

```

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```

6   'a1' | +0.56  +0.44  +0.50  +0.50  +0.44
7   'a2' | +0.56  +0.94  +0.19  +0.62  +0.62
8   'a3' | +0.81  +0.56  +0.12  +0.44  +0.31
9   'a4' | +0.56  +0.12  +0.44  +0.44  +0.94
10  'a5' | +0.19  +0.62  +0.94  +0.31  +0.31
11 Valuation domain: [-1.00;1.00]
12 >>> bcop.showPairing()
13 -----
14 ['a1', 'b4']
15 ['a2', 'b2']
16 ['a3', 'b1']
17 ['a4', 'b5']
18 ['a5', 'b3']

```

By following a kind of ranked pairs rule, we may construct in this graph a best determined bipartite maximal matching. The matches $[a_2, b_2]$, $[a_4, b_5]$ and $[a_5, b_3]$ show the highest Copeland scores (+0.94, see Lines 7,9-10), followed by $[a_3, b_1]$ (+0.81 Line 6). For Person a_1 , the best eventually available partner is b_4 (+0.50, line 6).

We are lucky here with the given example of reciprocal bipolar approval voting profiles $apA1$ and $apB1$ as we recover immediately the fairest enhanced matching obtained previously. The best determined *Copeland* matching is hence very opportune to take as initial start for the fairness enhancing procedure as it may similarly drastically reduce the potential number of fairness enhancing partner swappings (see Lines 3 and last below).

```

1 >>> fecop = FairnessEnhancedInterGroupMatching(
2 ...                               apA1,apB1,
3 ...                               initialMatching='bestCopeland',
4 ...                               Comments=False)
5 >>> fecop.showPairing()
6 -----
7 ['a1', 'b4']
8 ['a2', 'b2']
9 ['a3', 'b1']
10 ['a4', 'b5']
11 ['a5', 'b3']
12 >>> fecop.Iterations
13 0

```

A Monte Carlo simulation with 1000 intergroup pairing problems of order 6 with approval and disapproval probabilities of 30% shows actually that both starting points –*initialMatching* = *None* and *initialMatching* = ‘bestCopeland’– of the fairness enhancing heuristic may diverge positively and negatively in their respective best solutions.

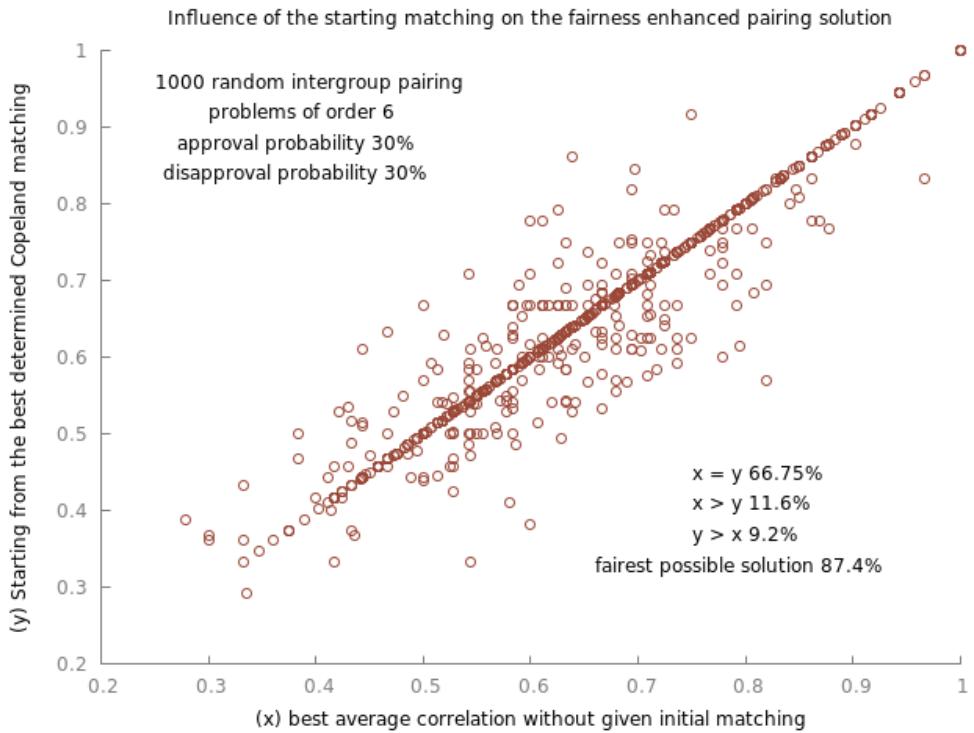


Fig. 2.36: Influence of the starting point on the fairness enhanced pairing solution

Discuss Fig. 2.36 fem 78.18% success rate fecop 75.78% success rate

If we run the fairness enhancing heuristic from both the left and right initial matchings as well as from the best determined Copeland matching and retain in fact the respective fairest solution of these three, we obtain, as shown in Fig. 2.37, a success rate of 87.39% for reaching the fairest possible pairing solution with an average failure of -0.036 and a maximum failure of -0.150.

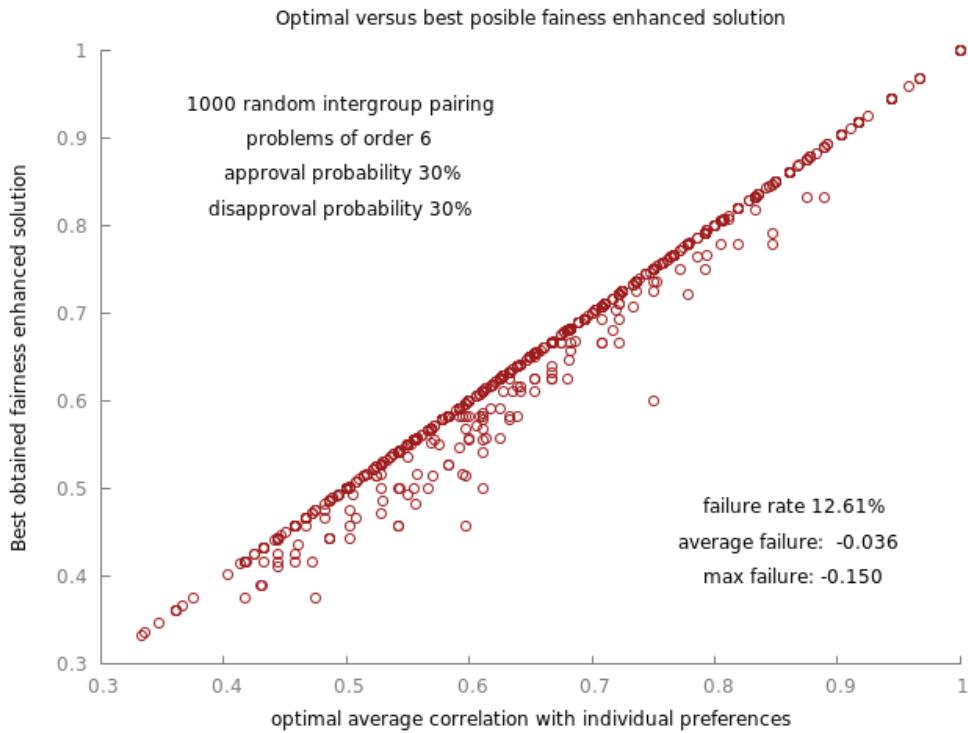


Fig. 2.37: Optimal versus best fairness enhanced pairing solution

For intergroup pairing problems of higher order, it appears however that the best determined *Copeland* matching gives in general a more efficient initial starting point for the fairness enhancing heuristic than both the left and right initial ones. In a Monte Carlo simulation with 1000 random bipolar approval pairing problems of order 50 and approval-disapproval probabilities of 20%, we obtain the results shown below.

Variables	Mean	Median	S.D.	Min	Max
Correlation	+0.886	+0.888	0.018	+0.850	+0.923
Unfairness	0.053	0.044	0.037	0.000	0.144
Run time (sec.)	1.901	1.895	0.029	1.868	2.142

The median overall average correlation with the individual pairing preferences amounts to +0.886 with a maximum at +0.923. The *Unfairness* statistic indicates the absolute difference between the average correlations obtained in group A versus group B.

In order to study the potential difference in quality and fairness of the pairing solutions obtained by starting the fairness enhancing procedure from both the left and right initial matching, from the best determined *Copeland* matching as well as from the fairest *Gale-Shapley* we ran a Monte Carlo simulation with 1000 random intergroup pairing problems of order 20 and where the individual pairing preferences were given with complete linear voting profiles (see Fig. 2.38).

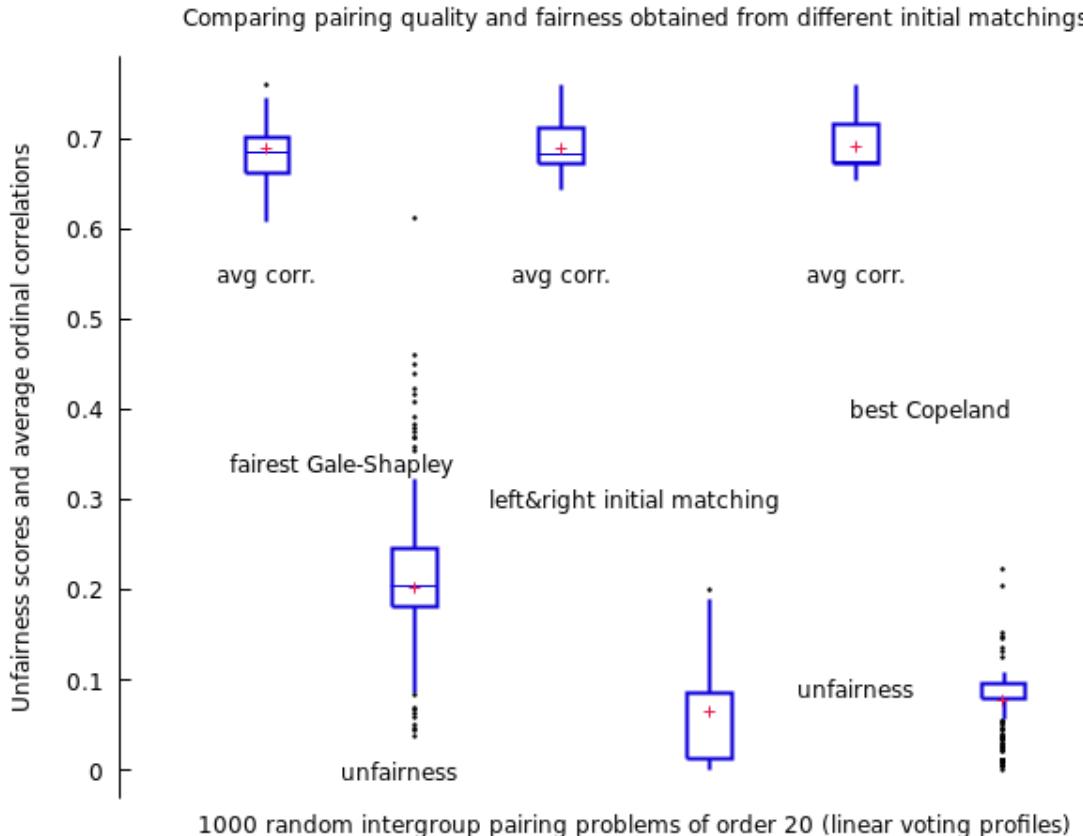


Fig. 2.38: Comparing pairing results from different fairnesss enhancing start points

If the average ordinal correlations obtained with the three starting matchings are quite similar –means within +0.690 and +0.693– the differences between the average correlations of group A and group B show a potential advantage for the left&right initial matchings (mean unfairness: 0.065) versus the best *Copeland* (mean unfairness: 0.078) and, even more versus the fairest *Gale-Shapley* matching (mean unfairness: 0.203, see Fig. 2.38). The essential unfairness of stable *Gale-Shapley* matchings may in fact not being corrected with our fairness enhancing procedure.

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2.10 On computing fair intragroup pairings

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- *Generating random intragroup bipolar approval voting profiles* (page 173)
- *The set of potential intragroup pairing decisions* (page 173)
- *Computing the fairest intragroup pairing* (page 174)

- Fairness enhancing of a given pairing decision (page 176)

The fair intragroup pairing problem

A very similar decision problem to the intergroup pairing one appears when, instead of pairing two different sets of persons, we are asked to pair an even-sized set of persons by fairly balancing again the individual pairing preferences of each person.

Let us consider a set of four persons $\{p_1, p_2, p_3, p_4\}$ to be paired. We may propose three potential pairing decisions :

- (1) p_1 with p_2 and p_3 with p_4 ,
- (2) p_1 with p_3 and p_2 with p_4 , and
- (3) p_1 with p_4 and p_2 with p_3 .

The individual pairing preferences, expressed under the format of bipolar approval ballots, are shown below:

```

1 Bipolar approval ballots
-----
2
3 p1 :
4 Approvals : ['p3', 'p4']
5 Disapprovals: ['p2']
6 p2 :
7 Approvals : ['p1']
8 Disapprovals: ['p3']
9 p3 :
10 Approvals : ['p1', 'p2', 'p4']
11 Disapprovals: []
12 p4 :
13 Approvals : ['p2']
14 Disapprovals: ['p1', 'p3']

```

Person p_1 , for instance, approves as potential partner both Persons p_3 and p_4 , but disapproves Person p_2 (see Lines 3-5). Person p_3 approves all potential partners, i.e. disapproves none of them (see Lines 9-11).

Out of the three potential pairing decision, which is the one that most fairly balances the given individual pairing preferences shown above? If we take decision (1), Person p_1 will be paired with a disapproved partner. If we take decision (3), Person p_2 will be paired with a disapproved partner. Only pairing decision (2) allocates no disapproved partner to all the persons.

We will generalise this approach to larger groups of persons in a similar way as we do in the intergroup pairing case.

Generating random intragroup bipolar approval voting profiles

Let us consider a group of six persons. Individual intragroup pairing preferences may be randomly generated with the `RandomBipolarApprovalVotingProfile` class by setting the `IntraGroup` parameter to `True` (see Line 6 below)

```
1  >>> from votingProfiles import\
2      ...             RandomBipolarApprovalVotingProfile
3  >>> vpG = RandomBipolarApprovalVotingProfile(
4      ...             numberOfWorkers=6,
5      ...             votersIdPrefix='p',
6      ...             IntraGroup=True,
7      ...             approvalProbability=0.5,
8      ...             disapprovalProbability=0.2,
9      ...             seed=1)
10 >>> vpG.showBipolarApprovals()
11 Bipolar approval ballots
12 -----
13 p1 :
14 Approvals : ['p4', 'p5']
15 Disapprovals: []
16 p2 :
17 Approvals : ['p1']
18 Disapprovals: ['p5']
19 p3 :
20 Approvals : []
21 Disapprovals: ['p2']
22 p4 :
23 Approvals : ['p1', 'p2', 'p3']
24 Disapprovals: ['p5']
25 p5 :
26 Approvals : ['p1', 'p2', 'p3', 'p6']
27 Disapprovals: ['p4']
28 p6 :
29 Approvals : ['p1', 'p2', 'p3', 'p4']
30 Disapprovals: []
```

With an approval probability of 50% and a disapproval probability of 20% we obtain the bipolar approvals shown above. Person p_1 approves p_4 and p_5 and disapproves nobody, whereas Person p_2 approves p_1 and disapproves p_5 (see Lines 14-15 and 17-18). To solve this intragroup pairing problem, we need to generate the set of potential matching decisions.

The set of potential intragroup pairing decisions

In the intergroup pairing problem, the potential pairing decisions are given by the maximal independent sets of the line graph of the bipartite graph formed between two even-sized groups of persons. Here the set of potential pairing decisions is given by the maximal

independents sets –the perfect matchings⁴⁸– of the line graph of the complete graph obtained from the given set of six persons (see below).

```

1  >>> persons = [p for p in vpG.voters]
2  >>> persons
3  ['p1', 'p2', 'p3', 'p4', 'p5', 'p6']
4  >>> from graphs import CompleteGraph, LineGraph
5  >>> cg = CompleteGraph(verticesKeys=persons)
6  >>> lcg = LineGraph(cg)
7  >>> lcg.computeMIS()
8  ... # result is stored into lcg.misset
9  >>> len(lcg.misset)
10 15
11 >>> lcg.misset[0]
12 frozenset({frozenset({'p5', 'p2'}),
13             frozenset({'p1', 'p6'}),
14             frozenset({'p3', 'p4'})})

```

In the intragroup case we observe 15 potential pairing decisions (see Line 10). For a set of persons of size $2 \times k$, the number of potential intragroup pairing decisions is actually given by the *double factorial of odd numbers*⁴⁷.

$$1 \times 3 \times 5 \times \dots \times (2 \times k - 1) = (2 \times k - 1)!!$$

For the first pair we have indeed $(2 \times k) - 1$ partner choices, for the second pair we have $(2 \times k) - 3$ partner choices, etc. This double factorial of odd numbers is far larger than the simple $k!$ number of potential pairing decisions in a corresponding intergroup pairing problem of order k .

In order to find now the fairest pairing among this potentially huge set of intragroup pairing decisions, we will reuse the same strategy as for the intergroup case. For each potential pairing solution, we are computing the average ordinal correlation between each potential pairing solution and the individual pairing preferences. The fairest pairing decision is eventually determined by the highest average coupled with the lowest standard deviation of the individual ordinal correlation indexes.

Computing the fairest intragroup pairing

For a pairing problem of tiny order ($2 \times k = 6$) we may use the `FairestIntraGroupPairing` class for computing in a brute force approach the fairest possible pairing solution :

```

1 >>> from pairings import FairestIntraGroupPairing
2 >>> fp = FairestIntraGroupPairing(vpG)
3 >>> fp.nbrOfMatchings
4 15

```

(continues on next page)

⁴⁸ A perfect matching is a saturated matching, i.e. a maximal matching which leaves no vertex unconnected.

⁴⁷ Integer sequence <http://oeis.org/A001147>

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```
5 >>> fp.showMatchingFairness()
6 Matched pairs
7 { 'p1', 'p4' }, { 'p3', 'p5' }, { 'p6', 'p2' }
8 -----
9 Individual correlations:
10 'p1': +1.000, 'p2': +0.000, 'p3': +1.000
11 'p4': +1.000, 'p5': +1.000, 'p6': +1.000
12 -----
13 Average correlation : +0.833
14 Unfairness (stdev)    : 0.408
```

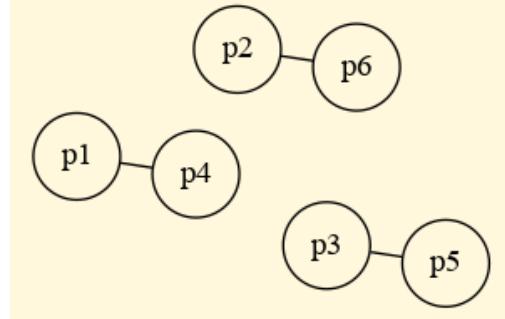
As expected, we observe with a problem of order 6 a set of $1 \times 3 \times 5 = 15$ potential pairings (see Line 4) and the fairest pairing solution –highest correlation (+0.833) with given individual pairing preferences– is shown in Line 7 above. All persons, except p_2 are paired with an approved partner and nobody is paired with a disapproved partner (see Lines 10-11).

In the intergroup pairing case, an indicator of the actual fairness of a pairing solution is given by the absolute difference between both group correlation values. In the intragroup case here, an indicator of the fairness is given by the standard deviation of the individual correlations (see Line 14). The lower this standard deviation with a same overall correlation result, the fairer appears to be in fact the pairing solution⁵⁰.

The `fp` object models in fact a generic `Graph` object whose edges correspond to the fairest possible pairing solution (see Lines 11-12). We may hence produce in Fig. 2.39 a drawing of the fairest pairing solution by using the standard `exportGraphViz()` method for undirected graphs.

```
>>> fp.exportGraphViz('fairestIntraGroupPairing')
*----- exporting a dot file for GraphViz tools -----*
Exporting to fairestIntraGroupPairing.dot
fdp -Tpng fairestIntraGroupPairing.dot -o fairestIntraGroupPairing.png
```

⁵⁰ The inter- and intragroup pairing solvers solely maximise the overall correlation with the individual pairing preferences. It may happen that a slightly lesser overall correlation result comes with a considerable lower standard deviation. Is this pairing solution than fairer than the one with a higher overall correlation? Asked more generally: is a society with highest global welfare but uneven wealth distribution a fairer society than the one showing less global welfare but with a considerable less uneven wealth distribution?



Digraph3 (graphviz), R. Bischoff, 2022

Fig. 2.39: Fairest intragroup pairing solution

Unfortunately, this brute force approach to find the fairest possible pairing solution fails in view of the explosive character of the double factorial of odd numbers. For a group of 20 persons, we observe indeed already more than 650 millions of potential pairing decisions. Similar to the intergroup pairing case, we may use instead a kind of hill climbing heuristic for computing a fair intragroup pairing solution.

Fairness enhancing of a given pairing decision

The `FairnessEnhancedIntraGroupMatching` class delivers such a solution. When no initial matching is given (see Line 3 below), our hill climbing strategy will start, similar to the intergroup pairing case, from two initial maximal matchings. The *left* one matches Person p_i with Person p_{i+1} for i in range 1 to 5 by step 3 (see Line 5-6) and the *right* one matches Person p_i with Person p_{-i} for i in range 1 to 3 (see Line 8-9).

```

1  >>> from pairings import FairnessEnhancedIntraGroupMatching
2  >>> fem = FairnessEnhancedIntraGroupMatching(vpG,
3  ...           initialMatching=None, Comments=True)
4  ===>>> Enhancing left initial matching
5  Initial left matching
6  [['p1', 'p2'], ['p3', 'p4'], ['p5', 'p6']]
7  Fairness enhanced left matching
8  [['p1', 'p4'], ['p3', 'p5'], ['p2', 'p6']] , correlation: 0.833
9  ===>>> Enhancing right initial matching
10 Initial right matching
11 [['p1', 'p6'], ['p3', 'p4'], ['p5', 'p2']]
12 Fairness enhanced right matching
13 [['p1', 'p4'], ['p3', 'p5'], ['p6', 'p2']] , correlation: 0.833
14 ===>>> Best fairness enhanced matching
15 Matched pairs
16 {'p1', 'p4'}, {'p2', 'p6'}, {'p3', 'p5'}
17 Average correlation: +0.833

```

The correlation enhancing search is similar to the one used for the intergroup heuristic. For each couple of pairs $\{p_i, p_j\}, \{p_r, p_s\}$ in the respective initial matchings we have in the intragroup case in fact **two** partners swapping opportunities: (1) $p_j \leftrightarrow p_s$ or, (2)

$pj <-> pr$. For both ways, we assess the expected individual correlation gains with the differences of the *Copeland* scores induced by the potential swappings. And we eventually proceed with a swapping of highest expected average correlation gain among all couple of pairs.

In the case of the previous bipolar approval intragroup voting profile vpG , both starting points for the hill climbing heuristic give the same solution, in fact the fairest possible pairing solution we have already obtained with the brute force algorithm in the preceding Section (see above).

To illustrate why starting from two initial matchings may be useful, we solve below a random intragroup pairing problem of order 20 where we assume an approval probability of 30% and a disapproval probability of 20% (see Line 3 below).

```

1  >>> vpG1 = RandomBipolarApprovalVotingProfile(
2      ...             numberOfVoters=20,votersIdPrefix='p',
3      ...             IntraGroup=True,approvalProbability=0.3,
4      ...             disapprovalProbability=0.2,seed=1)
5  >>> fem1 = FairnessEnhancedIntraGroupMatching(vpG1,
6      ...             initialMatching=None,Comments=True)
7  ====>>> Enhancing left initial matching
8  Initial left matching
9  [['p01', 'p02'], ['p03', 'p04'], ['p05', 'p06'], ['p07', 'p08'], ['p09',
10    ↪ 'p10'],
11  ['p11', 'p12'], ['p13', 'p14'], ['p15', 'p16'], ['p17', 'p18'], ['p19',
12    ↪ 'p20']]
13  Fairness enhanced left matching
14  [['p01', 'p02'], ['p03', 'p04'], ['p05', 'p15'], ['p06', 'p11'], ['p09',
15    ↪ 'p17'],
16  ['p07', 'p12'], ['p13', 'p14'], ['p08', 'p16'], ['p20', 'p18'], ['p19',
17    ↪ 'p10']],
18  correlation: +0.785
19  ====>>> Enhancing right initial matching
20  Initialright matching
21  [['p01', 'p20'], ['p03', 'p18'], ['p05', 'p16'], ['p07', 'p14'], ['p09',
22    ↪ 'p12'],
23  ['p11', 'p10'], ['p13', 'p08'], ['p15', 'p06'], ['p17', 'p04'], ['p19',
24    ↪ 'p02']]
25  Fairness enhanced right matching
26  [['p01', 'p19'], ['p03', 'p02'], ['p05', 'p15'], ['p07', 'p18'], ['p09',
27    ↪ 'p17'],
28  ['p14', 'p13'], ['p10', 'p04'], ['p08', 'p12'], ['p20', 'p16'], ['p06',
29    ↪ 'p11']],
30  correlation: +0.851
31  ====>>> Best fairness enhanced matching
32  Matched pairs
33  {'p01', 'p19'}, {'p03', 'p02'}, {'p05', 'p15'}, {'p06', 'p11'},
34  {'p07', 'p18'}, {'p08', 'p12'}, {'p09', 'p17'}, {'p10', 'p04'},
35

```

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```
27 {'p14', 'p13'}, {'p20', 'p16'}  
28 Average correlation: +0.851
```

The hill climbing from the left initial matching attains an average ordinal correlation of +0.785, whereas the one starting from the right initial matching improves this result to an average ordinal correlation of +0.851 (see Lines 14 and 22).

We may below inspect with the `showMatchingFairness()` method the individual ordinal correlation indexes obtained this way.

```
1 >>> fem1.showMatchingFairness(WithIndividualCorrelations=True)  
2 Matched pairs  
3 {'p01', 'p19'}, {'p03', 'p02'}, {'p05', 'p15'},  
4 {'p06', 'p11'}, {'p07', 'p18'}, {'p08', 'p12'},  
5 {'p09', 'p17'}, {'p10', 'p04'}, {'p14', 'p13'},  
6 {'p20', 'p16'}  
----  
8 Individual correlations:  
9 'p01': +1.000, 'p02': +1.000, 'p03': +1.000, 'p04': -0.143, 'p05': +1.  
10 ↪000,  
11 'p06': +1.000, 'p07': +0.500, 'p08': -0.333, 'p09': +1.000, 'p10': +1.  
12 ↪000,  
13 'p11': +1.000, 'p12': +1.000, 'p13': +1.000, 'p14': +1.000, 'p15': +1.  
14 ↪000,  
15 'p16': +1.000, 'p17': +1.000, 'p18': +1.000, 'p19': +1.000, 'p20': +1.  
↪000  
----  
14 Average correlation : +0.851  
15 Standard Deviation : 0.390
```

Only three persons –*p04*, *p07* and *p08*– are not matched with a mutually approved partner (see Lines 9-10 above). Yet, they are all three actually matched with a partner they neither approve nor disapprove but who in return approves them as partner (see Lines 10, 19 and 27 below).

```
1 >>> vpG1.showBipolarApprovals()  
2 Bipolar approval ballots  
3 -----  
4 ...  
5 ...  
6 p04 :  
7 Approvals : ['p03', 'p12', 'p14', 'p19']  
8 Disapprovals: ['p15', 'p18', 'p20']  
9 p10 :  
10 Approvals : ['p04', 'p17', 'p20']  
11 Disapprovals: ['p01', 'p02', 'p05', 'p06', 'p07', 'p08',  
12 'p09', 'p11', 'p12', 'p16', 'p18']
```

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```

13 ...
14 ...
15 p07 :
16 Approvals : ['p11']
17 Disapprovals: ['p01', 'p14', 'p19']
18 p12 :
19 Approvals : ['p06', 'p07', 'p08', 'p10', 'p16', 'p19']
20 Disapprovals: ['p11', 'p14']
21 ...
22 ...
23 p08 :
24 Approvals : ['p02', 'p05', 'p06', 'p14', 'p16', 'p19']
25 Disapprovals: ['p01', 'p13', 'p15']
26 p05 :
27 Approvals : ['p01', 'p04', 'p06', 'p07', 'p08', 'p11', 'p15', 'p16',
28 → 'p18']
29 Disapprovals: ['p13', 'p19']
30 ...

```

As the size of the potential maximal matchings with a pairing problem of order 20 exceeds 650 million instances, computing the overall fairest pairing solution becomes intractable and we are unable to check if we reached or not this optimal pairing solution. A Monte Carlo simulation with 1000 random intragroup pairing problem of order 8, applying an approval probability of 50% and a disapproval probability of 20%, shows however in Fig. 2.40 the apparent operational efficiency of our hill climbing heuristic, at least for small orders.

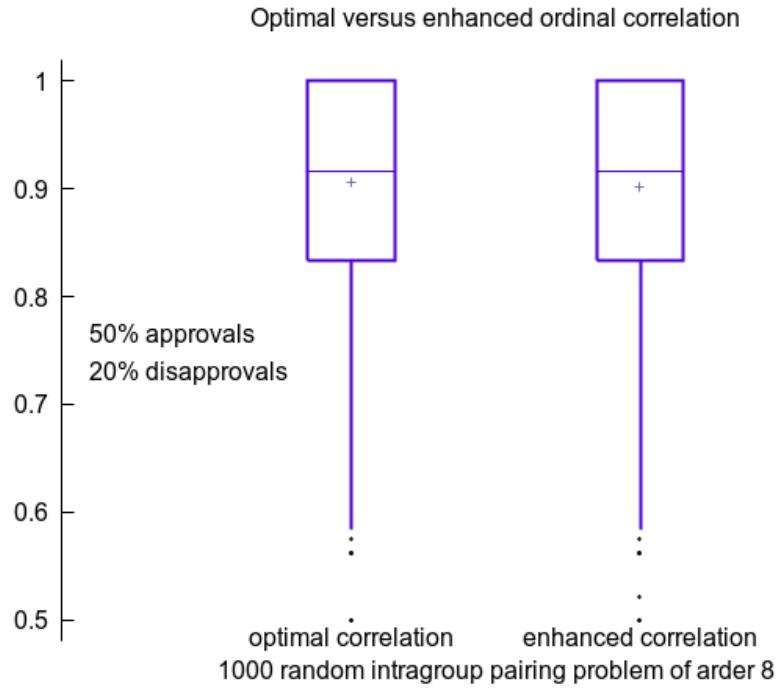


Fig. 2.40: Quality of fairness enhanced intragroup pairing solutions of order 8

Only 43 failures to reach the optimal average correlation were counted among the 1000 computations (4.3%) with a maximal difference in between of +0.250.

A similar simulation with more constrained random intragroup pairing problems of order 10, applying an approval and disapproval probability of only 30%, gives a failure rate of 19.1% to attain the optimal fairest pairing solution (see Fig. 2.41).

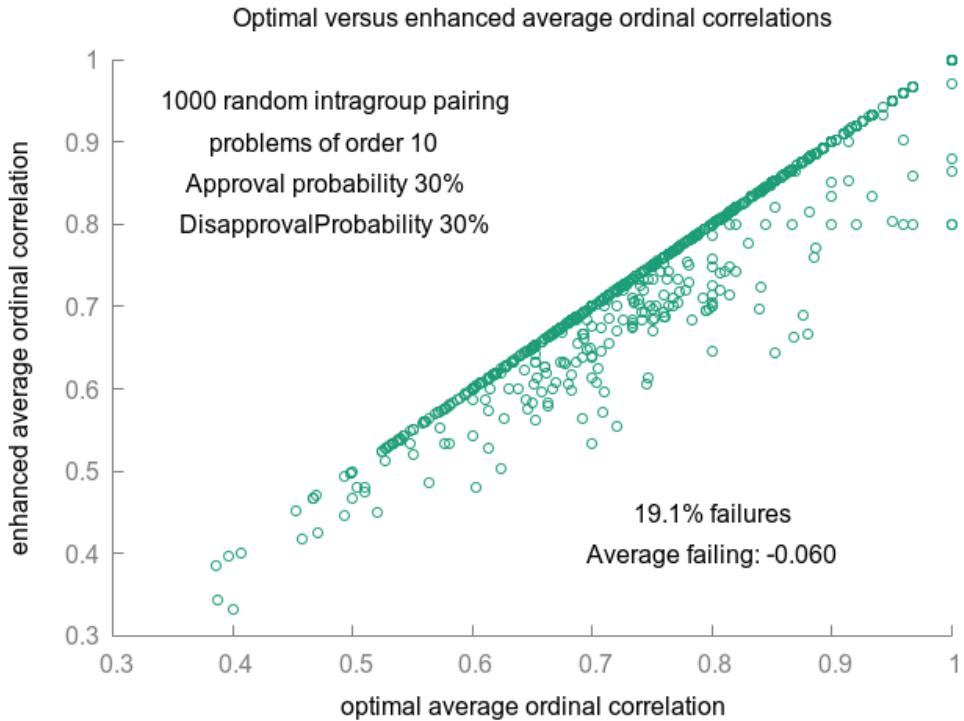


Fig. 2.41: Quality of fairness enhanced intragroup pairing solutions of order 10

Choosing, as in the intergroup pairing case, a more efficient initial matching for the fairness enhancing procedure becomes essential. For this purpose we may rely again on the best determined *Copeland* matching obtained with the pairwise *Copeland* scores computed on the complete intragroup graph. When we add indeed, for a pair $\{pi, pj\}$ both the *Copeland* ranking score of partner pj from the perspective of Person pi to the corresponding *Copeland* ranking score of partner pi from the perspective of Person pj we may obtain a complete positively valued graph object. In this graph we can, with a greedy ranked pairs rule, construct a best determined perfect matching which we may use as efficient initial start for the fairness enhancing heuristic (see below).

```

1 >>> from pairings import BestCopelandIntraGroupMatching
2 >>> cop = BestCopelandIntraGroupMatching(vpG1)
3 >>> cop.showPairing(cop.matching)
4 Matched pairs
5 {'p02', 'p15'}, {'p04', 'p03'}, {'p08', 'p05'}, {'p09', 'p20'}
6 {'p11', 'p06'}, {'p12', 'p16'}, {'p14', 'p13'}, {'p17', 'p10'}
7 {'p18', 'p07'}, {'p19', 'p01'}
8 >>> fem2 = FairnessEnhancedIntraGroupMatching(vpG1,
9 ...                               initialMatching=cop.matching,Comments=True)
10 *---- Initial matching ----*
11 [[['p02', 'p15'], ['p04', 'p03'], ['p08', 'p05'], ['p09', 'p20'],
12   ['p11', 'p06'], ['p12', 'p16'], ['p14', 'p13'], ['p17', 'p10'],
13   ['p18', 'p07'], ['p19', 'p01']]]
14 Enhancing iteration :  1
15 Enhancing iteration :  2

```

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```

16 ==>>> Best fairness enhanced matching
17 Matched pairs
18 {'p02', 'p04'}, {'p08', 'p05'}, {'p09', 'p20'},
19 {'p11', 'p06'}, {'p12', 'p16'}, {'p14', 'p13'},
20 {'p15', 'p03'}, {'p17', 'p10'}, {'p18', 'p07'},
21 {'p19', 'p01'}
22 Average correlation: +0.872
23 Total run time: 0.193 sec.

```

With the best determined *Copeland* matching we actually reach in two partner swappings a fairer pairing solution (+0.872) than the fairest one obtained with the default left and right initial matchings (+0.851). This is however not always the case. In order to check this issue, we ran a Monte Carlo experiment with 1000 random intragroup pairing problems of order 30 where approval and disapproval probabilities were set to 20%. Summary statistics of the results are shown in the Table below.

Variables	Mean	Median	S.D.	Min	Max
Correlation	+0.823	+0.825	0.044	+0.682	+0.948
Std deviation	0.361	0.362	0.051	0.186	0.575
Iterations	23.69	23.000	3.818	14.00	36.00
Run time	3.990	3.910	0.636	2.340	6.930

These statistics were obtained by trying both the left and right initial matchings as well as the best determined *Copeland* matching as starting point for the fairness enhancing procedure and keeping eventually the best average correlation result. The overall ordinal correlation hence obtained is convincingly high with a mean of +0.823, coupled with a reasonable mean standard deviation of 0.361 over the 30 personal correlations. Run times depend essentially on the number of enhancing iterations. On average, about 24 partner swappings were sufficient for computing all three variants in less than 4 seconds. In slightly more than two third only of the random pairing problems (69.4%), starting the fairness enhancing procedure from the best determined *Copeland* matching leads indeed to the best overall ordinal correlation with the individual pairing preferences.

When enhancing thus the fairness solely by starting from the best determined *Copeland* matching, we may solve with the `FairnessEnhancedIntraGroupMatching` solver in on average about 30 seconds an intragroup pairing problem of order 100 with random bipolar approval voting profiles and approval and disapproval probabilities of 10%. The average overall ordinal correlation we may obtain is about +0.800.

Mind however that the higher the order of the pairing problem, the more likely gets the fact that we actually may miss the overall fairest pairing solution. Eventually, a good expertise in metaheuristics is needed in order to effectively solve big intragroup pairing problems (*Avis aux amateurs*).

See also

Back to *Content Table* (page 1)

3 Evaluation and decision case studies

This part of the tutorails presents three decision making case studies, followed by a set of homework and exam questions.

- *Alice's best choice: A selection case study* (page 183)
- *The best academic Computer Science Depts: a ranking case study* (page 199)
- *The best students, where do they study? A rating case study* (page 221)
- *Classmates matching: An intragroup pairing case study* (page 235)
- *Fairest internship matching: An intergroup pairing case study* (page 242)
- *Exercises* (page 249)

3.1 Alice's best choice: A **selection** case study¹⁹

- *The decision problem* (page 184)
- *The performance tableau* (page 185)
- *Building a best choice recommendation* (page 188)
- *Robustness analysis* (page 195)



Alice D., 19 years old German student finishing her secondary studies in Köln (Germany), desires to undertake foreign languages studies. She will probably receive her 'Abitur' with satisfactory and/or good marks and wants to start her further studies thereafter.

¹⁹ This case study is inspired by a *Multiple Criteria Decision Analysis* case study published in Eisenführ Fr., Langer Th., and Weber M., *Fallstudien zu rationalem Entscheiden*, Springer 2001, pp. 1-17.

She would not mind staying in Köln, yet is ready to move elsewhere if necessary. The length of the higher studies do concern her, as she wants to earn her life as soon as possible. Her parents however agree to financially support her study fees, as well as, her living costs during her studies.

The decision problem

Alice has already identified 10 **potential study programs**.

Table 3.1: Alice's potential study programs

ID	Diploma	Institution	City
T-UD	Qualified translator (T)	University (UD)	Düsseldorf
T-FHK	Qualified translator (T)	Higher Technical School (FKH)	Köln
T-FHM	Qualified translator (T)	Higher Technical School (FHM)	München
I-FHK	Graduate interpreter (I)	Higher Technical School (FHK)	Köln
T-USB	Qualified translator (T)	University (USB)	Saarbrücken
I-USB	Graduate interpreter (I)	University (USB)	Saarbrücken
T-UHB	Qualified translator (T)	University (UHB)	Heidelberg
I-UHB	Graduate interpreter (I)	University (UHB)	Heidelberg
S-HKK	Specialized secretary (S)	Chamber of Commerce (HKK)	Köln
C-HKK	Foreign correspondent (C)	Chamber of Commerce (HKK)	Köln

In Table 3.1 we notice that Alice considers three *Graduate Interpreter* studies (8 or 9 Semesters), respectively in Köln, in Saarbrücken or in Heidelberg; and five *Qualified translator* studies (8 or 9 Semesters), respectively in Köln, in Düsseldorf, in Saarbrücken, in Heidelberg or in Munich. She also considers two short (4 Semesters) study programs at the Chamber of Commerce in Köln.

Four **decision objectives** of more or less equal importance are guiding Alice's choice:

1. *maximize* the attractiveness of the study place (GEO),
2. *maximize* the attractiveness of her further studies (LEA),
3. *minimize* her financial dependency on her parents (FIN),
4. *maximize* her professional perspectives (PRA).

The decision consequences Alice wishes to take into account for evaluating the potential study programs with respect to each of the four objectives are modelled by the following **coherent family of criteria**^{Page 34, 26}.

Table 3.2: Alice's family of performance criteria

ID	Name	Comment	Objective	Weight
DH	Proximity	Distance in km to her home (min)	GEO	3
BC	Big City	Number of inhabitants (max)	GEO	3
AS	Studies	Attractiveness of the studies (max)	LEA	6
SF	Fees	Annual study fees (min)	FIN	2
LC	Living	Monthly living costs (min)	FIN	2
SL	Length	Length of the studies (min)	FIN	2
AP	Profession	Attractiveness of the profession (max)	PRA	2
AI	Income	Annual income after studying (max)	PRA	2
PR	Prestige	Occupational prestige (max)	PRA	2

Within each decision objective, the performance criteria are considered to be equisignificant. Hence, the four decision objectives show a same importance weight of 6 (see Table 3.2).

The performance tableau

The actual evaluations of Alice's potential study programs are stored in a file named `AliceChoice.py` of `PerformanceTableau` format²¹.

Listing 3.1: Alice's performance tableau

```

1  >>> from perfTabs import PerformanceTableau
2  >>> t = PerformanceTableau('AliceChoice')
3  >>> t.showObjectives()
4      ----- decision objectives -----
5  GEO: Geographical aspect
6      DH Distance to parent's home 3
7      BC Number of inhabitants     3
8      Total weight: 6 (2 criteria)
9  LEA: Learning aspect
10     AS Attractiveness of the study program 6
11     Total weight: 6.00 (1 criteria)
12  FIN: Financial aspect
13     SF Annual registration fees 2

```

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²¹ Alice's performance tableau `AliceChoice.py` is available in the `examples` directory of the Digraph3 software collection.

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```

14 LC Monthly living costs      2
15 SL Study time              2
16 Total weight: 6.00 (3 criteria)
17 PRA: Professional aspect
18 AP Attractiveness of the profession      2
19 AI Annual professional income after studying 2
20 OP Occupational Prestige                2
21 Total weight: 6.00 (3 criteria)

```

Details of the performance criteria may be consulted in a browser view (see Fig. 3.1 below).

```
>>> t.showHTMLCriteria()
```

AliceChoice: Family of Criteria

#	Identifier	Name	Comment	Weight	Scale			Thresholds (ax + b)		
					direction	min	max	indifference	preference	veto
1	AI	Annual professional income after studying	Professional aspect measured in x / 1000 Euros	2.00	max	0.00	50.00	0.00x + 0.00	0.00x + 1.00	
2	AP	Attractiveness of the profession	Professional aspect subjectively measured on a three-level scale: 0 (weak), 1 (fair), 2 (good)	2.00	max	0.00	2.00	0.00x + 0.00	0.00x + 1.00	
3	AS	Attractiveness of the study program	Learning aspect subjectively measured from 0 (weak) to 10 (excellent)	6.00	max	0.00	10.00	0.00x + 0.00	0.00x + 1.00	0.00x + 7.00
4	BC	Number of inhabitants	Geographical aspect: measured in x / 1000	3.00	max	0.00	20000.00	0.01x + 0.00	0.05x + 0.00	
5	DH	Distance to parent's home	Geographical aspect measured in km	3.00	min	0.00	1000.00	0.00x + 0.00	0.00x + 10.00	
6	LC	Monthly living costs	Financial aspect measured in Euros	2.00	min	0.00	1000.00	0.00x + 0.00	0.00x + 100.00	
7	OP	Occupational Prestige	Professional aspect measured in SIOPS points	2.00	max	0.00	100.00	0.00x + 0.00	0.00x + 10.00	
8	SF	Annual registration fees	Financial aspect measured in Euros	2.00	min	400.00	4000.00	0.00x + 0.00	0.00x + 100.00	
9	SL	study time	Financial aspect measured in number of semesters	2.00	min	0.00	10.00	0.00x + 0.00	0.00x + 0.50	

Fig. 3.1: Alice's performance criteria

It is worthwhile noticing in Fig. 3.1 above that, on her subjective attractiveness scale of the study programs (criterion *AS*), Alice considers a performance difference of 7 points to be *considerable* and triggering, the case given, a *polarisation* of the outranking situation. Notice also the proportional *indifference* (1%) and *preference* (5%) discrimination thresholds shown on criterion *BC*-number of inhabitants.

In the following *heatmap view*, we may now consult Alice's performance evaluations.

```
>>> t.showHTMLPerformanceHeatmap(\n...     colorLevels=5, Correlations=True, ndigits=0)
```

Heatmap of Performance Tableau 'AliceChoice'

criteria	AS	AP	SF	OP	AI	DH	LC	BC	SL
weights	+6.00	+2.00	+2.00	+2.00	+2.00	+3.00	+2.00	+3.00	+2.00
tau(*)	+0.71	+0.64	+0.36	+0.36	+0.24	+0.03	-0.04	-0.07	-0.24
I-FHK	8	2	-400	62	35	0	0	1015	-8
I-USB	8	2	-400	62	45	-269	-1000	196	-9
T-FHK	5	1	-400	62	35	0	0	1015	-8
I-UHB	8	2	-400	62	45	-275	-1000	140	-9
T-UD	5	1	-400	62	45	-41	-1000	567	-9
T-USB	5	1	-400	62	45	-260	-1000	196	-9
T-FHM	4	1	-400	62	35	-631	-1000	1241	-8
T-UHB	5	1	-400	62	45	-275	-1000	140	-9
C-HKK	2	0	-4000	44	30	0	0	1015	-4
S-HKK	1	0	-4000	44	30	0	0	1015	-4

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
-----------------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation

Ranking rule: **NetFlows**

Ordinal (Kendall) correlation between global ranking and global outranking relation: **+0.692**

Fig. 3.2: Heatmap of Alice's performance tableau

Alice is subjectively evaluating the *Attractiveness* of the studies (criterion *AS*) on an ordinal scale from 0 (*weak*) to 10 (*excellent*). Similarly, she is subjectively evaluating the *Attractiveness* of the respective professions (criterion *AP*) on a three level ordinal scale from 0 (*weak*), 1 (*fair*) to 2 (*good*). Considering the *Occupational Prestige* (criterion *OP*), she looked up the SIOPS²⁰. All the other evaluation data she found on the internet (see Fig. 3.2).

Notice by the way that evaluations on performance criteria to be *minimized*, like *Distance to Home* (criterion *DH*) or *Study time* (criterion *SL*), are registered as *negative* values, so that smaller measures are, in this case, preferred to larger ones.

Her ten potential study programs are ordered with the *NetFlows* ranking rule applied to the corresponding bipolar-valued outranking digraph²³. *Graduate interpreter* studies in Köln (*I-FHK*) or Saarbrücken (*I-USB*), followed by *Qualified Translator* studies in Köln (*T-FHK*) appear to be Alice's most preferred alternatives. The least attractive study programs for her appear to be studies at the Chamber of Commerce of Köln (*C-HKK*, *S-HKK*).

It is finally interesting to observe in Fig. 3.2 (third row) that the *most significant* performance criteria, appear to be for Alice, on the one side, the *Attractiveness* of the study program (criterion *AS*, tau = +0.72) followed by the *Attractiveness* of the future profession (criterion *AP*, tau = +0.62). On the other side, *Study times* (criterion *SL*, tau =

²⁰ Ganzeboom H.B.G, Treiman D.J. "Internationally Comparable Measures of Occupational Status for the 1988 International Standard Classification of Occupations", *Social Science Research* 25, 201–239 (1996).

²³ See the tutorial on *ranking with multiple incommensurable criteria* (page 82).

-0.24), *Big city* (criterion BC , $\tau = -0.07$) as well as *Monthly living costs* (criterion LC , $\tau = -0.04$) appear to be for her *not so* significant²⁷.

Building a best choice recommendation

Let us now have a look at the resulting pairwise outranking situations.

Listing 3.2: Alice's outranking digraph

```

1  >>> from outrankingDigraphs import BipolarOutrankingDigraph
2  >>> dg = BipolarOutrankingDigraph(t)
3  >>> dg
4  *----- Object instance description -----*
5  Instance class      : BipolarOutrankingDigraph
6  Instance name       : rel_AliceChoice
7  # Actions           : 10
8  # Criteria          : 9
9  Size                : 67
10 Determinateness (%) : 73.91
11 Valuation domain   : [-1.00;1.00]
12 >>> dg.computeSymmetryDegree(Comments=True)
13 Symmetry degree of graph <rel_AliceChoice> : 0.49

```

From Alice's performance tableau we obtain 67 positively validated pairwise outranking situations in the digraph dg , supported by a 74% majority of criteria significance (see Listing 3.2 Line 9-10).

Due to the poorly discriminating performance evaluations, nearly half of these outranking situations (see Line 13) are *symmetric* and reveal actually *more or less indifference* situations between the potential study programs. This is well illustrated in the **relation map** of the outranking digraph (see Fig. 3.3).

```

>>> dg.showHTMLRelationMap(
...     tableTitle='Outranking relation map',
...     rankingRule='Copeland')

```

²⁷ See also the corresponding Advanced Topic in the Digraph3 documentation.

Outranking relation map

Ranking rule: Copeland

$r(x \leq y)$	I-FHK	I-USB	I-UHB	T-FHK	T-UD	T-USB	T-UHB	T-FHM	C-HKK	S-HKK
I-FHK			.	+	+
I-USB	.		+	.	.	.	+	.	.	+
I-UHB	+	.	.	+
T-FHK
T-UD	-	.	.	.		+	+	.	.	.
T-USB	-		+	.	.	.
T-UHB	-	-
T-FHM	-	-	-
C-HKK	-	-	-	-	-	-	-	-		+
S-HKK	—	—	—	-	-	-	-	-	-	—

Semantics

+	certainly valid
.	valid
	indeterminate
-	invalid
—	certainly invalid

Fig. 3.3: ‘Copeland’-ranked outranking relation map

We have mentioned that Alice considers a performance difference of 7 points on the *Attractiveness of studies* criterion *AS* to be considerable which triggers, the case given, a potential polarisation of the outranking characteristics. In Fig. 3.3 above, these polarisations appear in the last column and last row. We may inspect the occurrence of such polarisations as follows.

Listing 3.3: Polarised outranking situations

```

1 >>> dg.showPolarisations()
2 ----- Negative polarisations ----*
3 number of negative polarisations : 3
4 1: r(S-HKK >= I-FHK) = -0.17
5 criterion: AS
6 Considerable performance difference : -7.00
7 Veto discrimination threshold : -7.00
8 Polarisation: r(S-HKK >= I-FHK) = -0.17 ==> -1.00
9 2: r(S-HKK >= I-USB) = -0.17
10 criterion: AS
11 Considerable performance difference : -7.00
12 Veto discrimination threshold : -7.00
13 Polarisation: r(S-HKK >= I-USB) = -0.17 ==> -1.00
14 3: r(S-HKK >= I-UHB) = -0.17
15 criterion: AS

```

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```

16 Considerable performance difference : -7.00
17 Veto discrimination threshold      : -7.00
18 Polarisation: r(S-HKK >= I-UHB) = -0.17 ==> -1.00
19 *---- Positive polarisations ----*
20 number of positive polarisations: 3
21 1: r(I-FHK >= S-HKK) = 0.83
22 criterion: AS
23 Considerable performance difference : 7.00
24 Counter-veto threshold          : 7.00
25 Polarisation: r(I-FHK >= S-HKK) = 0.83 ==> +1.00
26 2: r(I-USB >= S-HKK) = 0.17
27 criterion: AS
28 Considerable performance difference : 7.00
29 Counter-veto threshold          : 7.00
30 Polarisation: r(I-USB >= S-HKK) = 0.17 ==> +1.00
31 3: r(I-UHB >= S-HKK) = 0.17
32 criterion: AS
33 Considerable performance difference : 7.00
34 Counter-veto threshold          : 7.00
35 Polarisation: r(I-UHB >= S-HKK) = 0.17 ==> +1.00

```

In Listing 3.3, we see that *considerable performance differences* concerning the *Attractiveness of the studies* (AS criterion) are indeed observed between the *Specialised Secretary* study programm offered in Köln and the *Graduate Interpreter* study programs offered in Köln, Saarbrücken and Heidelberg. They polarise, hence, three *more or less invalid* outranking situations to *certainly invalid* (Lines 8, 13, 18) and corresponding three *more or less valid* converse outranking situations to *certainly valid* ones (Lines 25, 30, 35).

We may furthermore notice in Fig. 3.3, that the four first-ranked study programs, *I-FHK*, *I-USB*, *I-UHB* and *T-FHK*, are in fact *Condorcet* winners (see Listing 3.4 Line 2), i.e. they are all four *indifferent* one of the other **and** they positively *outrank* all other alternatives, a result confirmed below by our best choice recommendation (Line 8).

Listing 3.4: Alice's best choice recommendation

```

1 >>> dg.computeCondorcetWinners()
2 ['I-FHK', 'I-UHB', 'I-USB', 'T-FHK']
3 >>> dg.showBestChoiceRecommendation()
4 Best choice recommendation(s) (BCR)
5 (in decreasing order of determinateness)
6 Credibility domain: [-1.00,1.00]
7 === >> potential first choice(s)
8 choice           : ['I-FHK', 'I-UHB', 'I-USB', 'T-FHK']
9 independence    : 0.17
10 dominance       : 0.08
11 absorbency      : -0.83
12 covering (%)   : 62.50

```

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```

13 determinateness (%) : 68.75
14 most credible action(s) = {'I-FHK': 0.75, 'T-FHK': 0.17,
15                               'I-USB': 0.17, 'I-UHB': 0.17}
16 === >> potential last choice(s)
17 choice : ['C-HKK', 'S-HKK']
18 independence : 0.50
19 dominance : -0.83
20 absorbency : 0.17
21 covered (%) : 100.00
22 determinateness (%) : 58.33
23 most credible action(s) = {'S-HKK': 0.17, 'C-HKK': 0.17}

```

Notice in Line 14 above that the most credible best choice among the four first-ranked study programs eventually becomes the *Graduate Interpreter* study program at the *Technical High School* in *Köln* supported by a $(0.75 + 1)/2.0 = 87.5\%$ ($18/24$) majority of global criteria significance²⁴.

In the relation map, shown in Fig. 3.3 above, we finally see in the left corner that the *asymmetrical* part of the outranking relation, i.e. the corresponding *strict* outranking relation, is actually *transitive* (see Lines 3-6 in Listing 3.5). We can hence make usage of the `showTransitiveDigraph()` method from the `transitiveDigraphs.TransitiveDigraph` to illustrate our previous first choice recommendation.

Listing 3.5: The asymmetrical outranking is transitive

```

1 >>> cdg = ~(dg) # codual == strict outranking digraph
2 >>> cdg.computeTransitivityDegree(Comments=True)
3 Transitivity degree of digraph <converse-dual-rel_AliceChoice>:
4   #triples x>y>z: 14, #closed: 14, #open: 0
5   (#closed/#triples) = 1.000
6   Decimal('1')
7 >>> from transitiveDigraphs import TransitiveDigraph
8 >>> TransitiveDigraph.showTransitiveDigraph(cdg)
9 Ranking by Choosing and Rejecting
10  1st ranked ['I-FHK', 'I-UHB', 'I-USB', 'T-FHK']
11  2nd ranked ['T-FHM', 'T-UD', 'T-UHB', 'T-USB']
12  2nd last ranked ['T-FHM', 'T-UD', 'T-UHB', 'T-USB'])
13  1st last ranked ['C-HKK', 'S-HKK'])
14 >>> TransitiveDigraph.exportGraphViz(cdg,
15           'strictOutranking')
16 *---- exporting a dot file for GraphViz tools -----
17 Exporting to strictOutranking.dot
18 0 subgraph { rank=same ; I_FHK; I_UHB; I_USB; T_FHK; }
19 1 subgraph { rank=same; T_UHB; T_USB; T_UD; T_FHM; }
20 2 subgraph { rank=same; S_HKK; C_HKK; }

```

(continues on next page)

²⁴ See also the Advanced Topic about computing best choice membership characteristics in the `Di-graph3` documentation.

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```
21 dot -Grankdir=TB -Tpng strictOutranking.dot -o strictOutranking.png
```

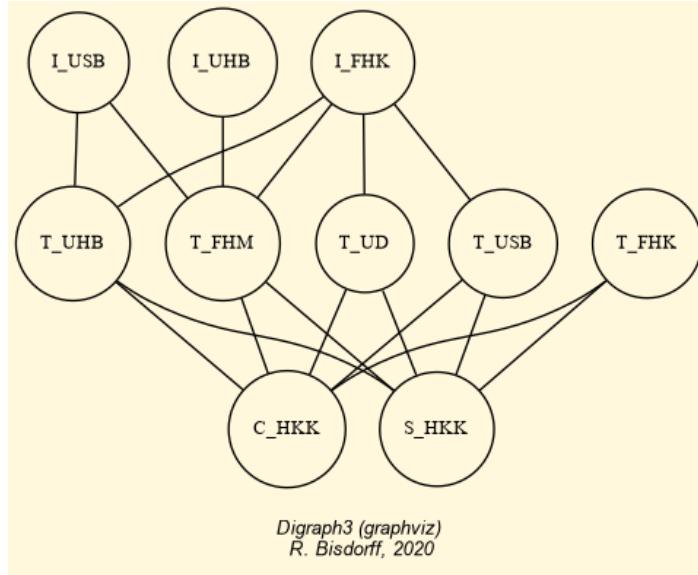


Fig. 3.4: The strict outranking relation

In Listing 3.5 and in Fig. 3.4 we find actually confirmed that all the *Graduate Interpreter* studies come first, followed by the *Qualified Translator* studies. Last come the *Köln Chamber of Commerce's* specialized studies. This confirms again the high significance Alice attaches to the *attractiveness* of her further studies and of her future profession (see criteria *AS* and *AP* in Fig. 3.2).

Let us now, for instance, check the pairwise outranking situations observed between the *Graduate Interpreter* studies in *Köln* and the *Graduate Interpreter* studies in *Saarbrücken* (see *I-FHK* and *I-USB* in Fig. 3.2).

```
>>> dg.showHTMLPairwiseOutrankings('I-FHK', 'I-USB')
```

Pairwise Comparison

Comparing actions : (I-FHK,I-USB)

crit.	wght.	g(x)	g(y)	diff	ind	pref	concord	v	polarisation
AI	2.00	35.00	+45.00	-10	0.00	1.00	-2.00		
AP	2.00	2.00	+2.00	0	0.00	1.00	+2.00		
AS	6.00	8.00	+8.00	0	0.00	1.00	+6.00		
BC	3.00	1015.00	+196.00	819	10.15	50.75	+3.00		
DH	3.00	0.00	-269.00	269	0.00	10.00	+3.00		
LC	2.00	0.00	-1000.00	1000	0.00	100.00	+2.00		
OP	2.00	62.00	+62.00	0	0.00	10.00	+2.00		
SF	2.00	-400.00	-400.00	0	0.00	100.00	+2.00		
SL	2.00	-8.00	-9.00	1	0.00	0.50	+2.00		

Valuation in range: -24.00 to +24.00; global concordance: +20.00

Pairwise Comparison

Comparing actions : (I-USB,I-FHK)

crit.	wght.	g(x)	g(y)	diff	ind	pref	concord	v	polarisation
AI	2.00	45.00	+35.00	10	0.00	1.00	+2.00		
AP	2.00	2.00	+2.00	0	0.00	1.00	+2.00		
AS	6.00	8.00	+8.00	0	0.00	1.00	+6.00		
BC	3.00	196.00	+1015.00	-819	10.15	50.75	-3.00		
DH	3.00	-269.00	+0.00	-269	0.00	10.00	-3.00		
LC	2.00	-1000.00	+0.00	-1000	0.00	100.00	-2.00		
OP	2.00	62.00	+62.00	0	0.00	10.00	+2.00		
SF	2.00	-400.00	-400.00	0	0.00	100.00	+2.00		
SL	2.00	-9.00	-8.00	-1	0.00	0.50	-2.00		

Valuation in range: -24.00 to +24.00; global concordance: +4.00

Fig. 3.5: Comparing the first and second best-ranked study programs

The *Köln* alternative is performing **at least as well as** the *Saarbrücken* alternative on all the performance criteria, except the *Annual income* (of significance 2/24). Conversely, the *Saarbrücken* alternative is clearly **outperformed** from the *geographical* (0/6) as well as from the *financial* perspective (2/6) (see Fig. 3.1).

In a similar way, we may compute a *partial ranking* of all the potential study programs with the help of the `PartialBachetRankingDigraph` class (see Listing 3.6 Line 2 below), which computes a *partial transitive ranking consensus* (page 102) of the five best qualified Bachet rankings. Such partial transitive digraphs may be shown by **recursively extracting** initial and terminal kernels [BIS-1999].

Listing 3.6: Partial ranking from a Bachet rankings consensus

```

1  >>> from transitiveDigraphs import PartialBachetRankingDigraph
2  >>> pbr = PartialBachetRanking(dg,randomized=100,maxNbrOfRankings=5,
    (continues on next page)

```

(continued from previous page)

```

1 →seed=1)
2 >>> pbr.bachetRankings
3 [(+0.715,['I-FHK','I-USB','T-FHK','I-UHB','T-UD','T-USB','T-UHB','T-FHM
4 ←','C-HKK','S-HKK']),+
5 (+0.700,['I-FHK','I-USB','T-FHK','T-UD','T-USB','I-UHB','T-UHB','T-FHM
6 ←','C-HKK','S-HKK']),+
7 (+0.698,['I-FHK','I-UHB','I-USB','T-FHK','T-UD','T-USB','T-UHB','T-FHM
8 ←','C-HKK','S-HKK']),+
9 (+0.692,['I-FHK','I-USB','I-UHB','T-FHK','T-UD','T-USB','T-UHB','T-FHM
10 ←','S-HKK','C-HKK']),+
11 (+0.684,['I-FHK','I-USB','T-FHK','T-USB','I-UHB','T-UD','T-UHB','T-FHM
12 ←','C-HKK','S-HKK'])]
13 >>> pbr.showTransitiveDigraph()
14 Ranking by Choosing and Rejecting
15 1st ranked ['I-FHK']
16 2nd ranked ['I-UHB', 'I-USB']
17 3rd ranked ['T-FHK']
18 4th ranked ['T-UD', 'T-USB']
19 4th last ranked ['T-UD', 'T-USB'])
20 3rd last ranked ['T-UHB'])
21 2nd last ranked ['T-FHM'])
22 1st last ranked ['C-HKK', 'S-HKK'])
23 >>> dg.showCorrelation(dg.computeOrdinalCorrelation(pbr))
24 Correlation indexes:
25 Crisp ordinal correlation : +0.799
26 Epistemic determination : 0.405
27 Bipolar-valued equivalence : +0.323

```

In Listing 3.6, we find confirmed that the *Köln Interpreter* studies appear always first-ranked (Lines 4-8) and all the *Interpreter* studies are preferred to the *Translator* studies (Lines 11-12). The *Köln Translator* studies are the preferred ones of all the *Translator* studies (Line 13). The *Foreign Correspondent* and the *Specialised Secretary* studies both appear last-ranked (Line 18). Notice by the way the high ordinal correlations of each one of the five *Bachet* rankings with the digraph *dg* (Lines 4-8). Their ranking consensus is hence also highly correlated with the given outranking digraph *dg* (+0.80) and supported by a criteria significance majority of 66% (Lines 21-23).

```

1 >>> pbr.exportGraphViz('AlliceBestChoice')
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to AlliceBestChoice.dot
4 dot -Grankdir=TB -Tpng AlliceBestChoice.dot -o AlliceBestChoice.png

```

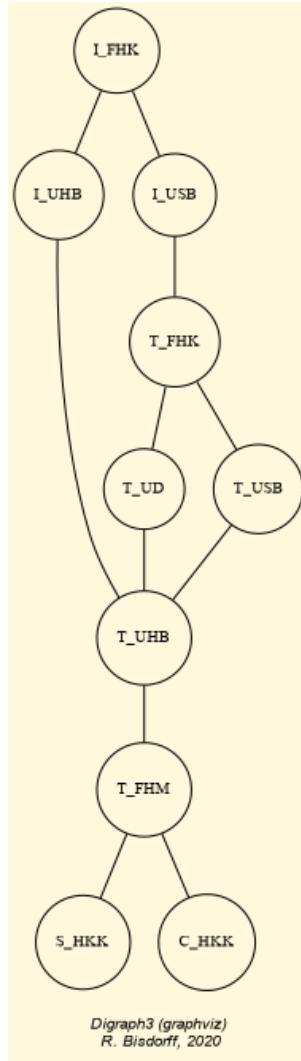


Fig. 3.6: Partial ranking of the study programs

In Fig. 3.6 we find the corresponding drawing of the partial ranking of the ten further study alternatives. We may notice there that the *Heidelberg* Interpreter studies do not compare well with the studies in *Saarbrücken*, *Düsseldorf* or *Köln*.

Yet, how *robust* are our findings with respect to potential settings of the decision objectives' importance and the performance criteria significance ?

Robustness analysis

Alice considers her four decision objectives as being *more or less* equally important. Here we have, however, allocated *strictly equal* importance weights with *strictly equi-significant* criteria per objective. How robust is our previous best choice recommendation when, now, we would consider the importance of the objectives and, hence, the significance of the respective performance criteria to be *more or less uncertain* ?

To answer this question, we will consider the respective criteria significance weights w_j to be **triangular random variables** in the range 0 to $2w_j$ with $mode = w_j$. We may compute a corresponding **90%-confident outranking digraph** with the help of the

`ConfidentBipolarOutrankingDigraph` constructor²².

Listing 3.7: The 90% confident outranking digraph

```
1 >>> from outrankingDigraphs import\  
2 ...     ConfidentBipolarOutrankingDigraph  
3 >>> cdg = ConfidentBipolarOutrankingDigraph(t,  
4 ...         distribution='triangular',confidence=90.0)  
5 >>> cdg  
6 *----- Object instance description -----*  
7 Instance class      : ConfidentBipolarOutrankingDigraph  
8 Instance name       : rel_AliceChoice_CLT  
9 # Actions           : 10  
10 # Criteria          : 9  
11 Size                : 44  
12 Valuation domain    : [-1.00;1.00]  
13 Uncertainty model   : triangular(a=0,b=2w)  
14 Likelihood domain   : [-1.0;+1.0]  
15 Confidence level    : 90.0%  
16 Confident credibility: > abs(0.167) (58.3%)  
17 Determinateness (%) : 68.19
```

Of the original 67 valid outranking situations, we retain 44 outranking situations as being *90%-confident* (see Listing 3.7 Line 11). The corresponding *90%-confident qualified majority* of criteria significance amounts to $14/24 = 58.3\%$ (Line 15).

Concerning now a *90%-confident* best choice recommendation, we are lucky (see Listing 3.8 below).

Listing 3.8: The 90% confident best choice recommendation

```
1 >>> cdg.computeCondorcetWinners()  
2 ['I-FHK']  
3 >>> cdg.showBestChoiceRecommendation()  
4 *****  
5 Best choice recommendation(s) (BCR)  
6 (in decreasing order of determinateness)  
7 Credibility domain: [-1.00,1.00]  
8 === >> potential first choice(s)  
9 choice        : ['I-FHK','I-UHB','I-USB',  
10             'T-FHK','T-FHM']  
11 independence   : 0.00  
12 dominance      : 0.42  
13 absorbency     : 0.00  
14 covering (%)   : 20.00  
15 determinateness (%) : 61.25  
16 - most credible action(s) = { 'I-FHK': 0.75, }
```

²² See also the corresponding Advanced Topic in the Digraph3 documentation.

The *Graduate Interpreter* studies in Köln remain indeed a 90%-confident Condorcet winner (Line 2). Hence, the same study program also remains our 90%-confident most credible best choice supported by a continual 18/24 (87.5%) majority of the global criteria significance (see Lines 9-10 and 16).

When previously comparing the two best-ranked study programs (see Fig. 3.5), we have observed that *I-FHK* actually positively outranks *I-USB* on all four decision objectives. When admitting equi-significant criteria significance weights per objective, this outranking situation is hence valid independently of the importance weights Alice may allocate to each of her decision objectives.

We may compute these **unopposed** outranking situations²⁵ with help of the `UnOpposedBipolarOutrankingDigraph` constructor.

Listing 3.9: Computing the unopposed outranking situations

```

1 >>> from outrankingDigraphs import UnOpposedBipolarOutrankingDigraph
2 >>> uop = UnOpposedBipolarOutrankingDigraph(t)
3 >>> uop
4 *----- Object instance description -----*
5     Instance class      : UnOpposedBipolarOutrankingDigraph
6     Instance name       : AliceChoice_unopposed_outrankings
7     # Actions           : 10
8     # Criteria          : 9
9     Size                : 28
10    Oppositeness (%)   : 58.21
11    Determinateness (%) : 62.94
12    Valuation domain   : [-1.00;1.00]
13 >>> uop.isTransitive()
14 True

```

We keep 28 out the 67 standard outranking situations, which leads to an **oppositeness degree** of $(1.0 - 28/67) = 58.21\%$ (Listing 3.9 Line 10). Remarkable furthermore is that this unopposed outranking digraph *uop* is actually *transitive*, i.e. modelling a *partial ranking* of the study programs (Line 14).

We may hence use the `exportGraphViz()` method of the `TransitiveDigraph` class for drawing the corresponding partial ranking.

```

1 >>> from transitiveDigraphs import TransitiveDigraph
2 >>> TransitiveDigraph.exportGraphViz(uop, ArrowHeads=True,
3 ...           fileName='choice_unopposed')
4 *----- exporting a dot file for GraphViz tools -----*
5 Exporting to choice_unopposed.dot
6 dot -Grankdir=TB -Tpng choice_unopposed.dot -o choice_unopposed.png

```

²⁵ See also the corresponding Advanced Topic in the Digraph3 documentation.

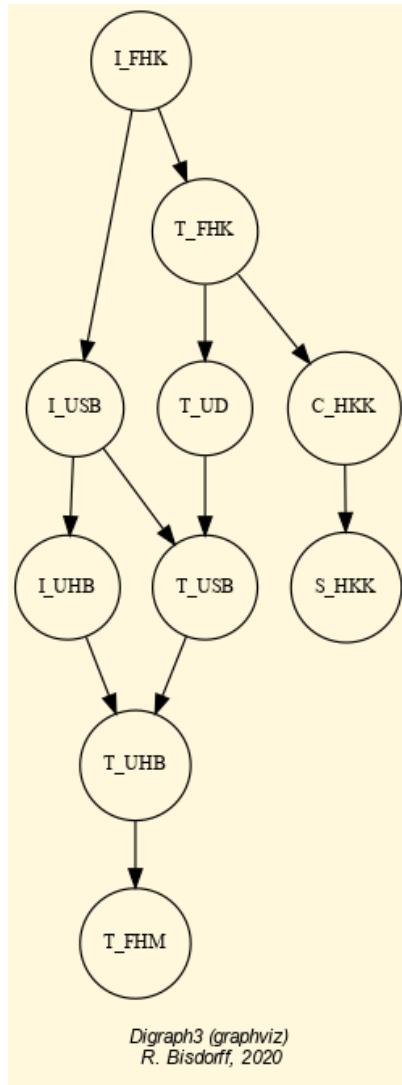


Fig. 3.7: Unopposed partial ranking of the potential study programs

Again, when *equi-significant* performance criteria are assumed per decision objective, we observe in Fig. 3.7 that *I-FHK* remains the stable best choice, *independently* of the actual importance weights that Alice may wish to allocate to her four decision objectives.

In view of her performance tableau in Fig. 3.2, *Graduate Interpreter* studies at the *Technical High School Köln*, thus, represent definitely **Alice's very best choice**.

For further reading about the Best Choice methodology, one may consult in [BIS-2015] the study of a *real decision aid case* about choosing a best poster in a scientific conference.

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3.2 The best academic *Computer Science* Depts: a *ranking* case study

- *The THE performance tableau* (page 199)
- *Ranking with multiple incommensurable criteria of ordinal significance* (page 205)
- *How to judge the quality of a ranking result?* (page 213)

In this tutorial, we are studying a ranking decision problem based on published data from the *Times Higher Education* (THE) *World University Rankings* 2016 by *Computer Science* (CS) subject³⁶. Several hundred academic CS Departments, from all over the world, were ranked that year following an overall numerical score based on the weighted average of five performance criteria: *Teaching* (the learning environment, 30%), *Research* (volume, income and reputation, 30%), *Citations* (research influence, 27.5%), *International outlook* (staff, students, and research, 7.5%), and *Industry income* (innovation, 5%).

To illustrate our *Digraph3* programming resources, we shall first have a look into the THE ranking data with short Python scripts. In a second Section, we shall relax the commensurability hypothesis of the ranking criteria and show how to similarly rank with multiple incommensurable performance criteria of ordinal significance. A third Section is finally devoted to introduce quality measures for qualifying ranking results.

The THE performance tableau

For our tutorial purpose, an extract of the published THE University rankings 2016 by computer science subject data, concerning the 75 first-ranked academic Institutions, is stored in a file named `the_cs_2016.py` of `PerformanceTableau` format³⁷.

Listing 3.10: The 2016 THE World University Ranking
by CS subject

```
1  >>> from perfTabs import PerformanceTableau
2  >>> t = PerformanceTableau('the_cs_2016')
3  >>> t
4  *----- PerformanceTableau instance description -----*
5  Instance class      : PerformanceTableau
6  Instance name       : the_cs_2016
7  # Actions           : 75
8  # Objectives        : 5
9  # Criteria          : 5
10 NaN proportion (%) : 0.0
11 Attributes         : ['name', 'description', 'actions',
(continues on next page)
```

³⁶ https://www.timeshighereducation.com/world-university-rankings/2017/subject-ranking/computer-science#/!page/0/length/25/sort_by/rank/sort_order/asc/cols/scores

³⁷ The performance tableau `the_cs_2016.py` is also available in the `examples` directory of the `Digraph3` software collection.

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```
12     'objectives', 'criteria',
13     'weightPreorder', 'NA', 'evaluation']
```

Potential *decision actions*, in our case here, are the 75 THE best-ranked *CS Departments*, all of them located at world renowned Institutions, like *California Institute of Technology*, *Swiss Federal Institute of Technology Zurich*, *Technical University München*, *University of Oxford* or the *National University of Singapore* (see Listing 3.11 below).

Instead of using prefigured *Digraph3 show* methods, readily available for inspecting *PerformanceTableau* instances, we will illustrate below how to write small Python scripts for printing out its content.

Listing 3.11: Printing the potential decision actions

```
1 >>> for x in t.actions:
2 ...     print('%s:\t%s (%s)' %\
3 ...           (x,t.actions[x]['name'],t.actions[x]['comment'])) 
4
5 albt:      University of Alberta (CA)
6 anu:       Australian National University (AU)
7 ariz:      Arizona State University (US)
8 bju:       Beijing University (CN)
9 bro:       Brown University (US)
10 calt:     California Institute of Technology (US)
11 cbu:      Columbia University (US)
12 chku:     Chinese University of Hong Kong (HK)
13 cihk:     City University of Hong Kong (HK)
14 cir:      University of California at Irvine (US)
15 cmel:     Carnegie Mellon University (US)
16 cou:      Cornell University (US)
17 csb:      University of California at Santa Barbara (US)
18 csd:      University Of California at San Diego (US)
19 dut:      Delft University of Technology (NL)
20 eind:     Eindhoven University of Technology (NL)
21 ens:      Superior Normal School at Paris (FR)
22 epfl:     Swiss Federal Institute of Technology Lausanne (CH)
23 epfr:     Polytechnic school of Paris (FR)
24 ethz:     Swiss Federal Institute of Technology Zurich (CH)
25 frei:     University of Freiburg (DE)
26 git:      Georgia Institute of Technology (US)
27 glas:     University of Glasgow (UK)
28 hels:     University of Helsinki (FI)
29 hkpu:    Hong Kong Polytechnic University (CN)
30 hkst:    Hong Kong University of Science and Technology (HK)
31 hku:     Hong Kong University (HK)
32 humb:    Berlin Humboldt University (DE)
33 icl:     Imperial College London (UK)
```

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34 indis:	Indian Institute of Science (IN)
35 itmo:	ITMO University (RU)
36 kcl:	King's College London (UK)
37 kist:	Korea Advances Institute of Science and Technology (KR)
38 kit:	Karlsruhe Institute of Technology (DE)
39 kth:	KTH Royal Institute of Technology (SE)
40 kuj:	Kyoto University (JP)
41 kul:	Catholic University Leuven (BE)
42 lms:	Lomonosov Moscow State University (RU)
43 man:	University of Manchester (UK)
44 mcp:	University of Maryland College Park (US)
45 mel:	University of Melbourne (AU)
46 mil:	Polytechnic University of Milan (IT)
47 mit:	Massachusetts Institute of Technology (US)
48 naji:	Nanjing University (CN)
49 ntu:	Nanyang Technological University of Singapore (SG)
50 ntw:	National Taiwan University (TW)
51 nyu:	New York University (US)
52 oxf:	University of Oxford (UK)
53 pud:	Purdue University (US)
54 qut:	Queensland University of Technology (AU)
55 rcu:	Rice University (US)
56 rwth:	RWTH Aachen University (DE)
57 shJi:	Shanghai Jiao Tong University (CN)
58 sing:	National University of Singapore (SG)
59 sou:	University of Southampton (UK)
60 stut:	University of Stuttgart (DE)
61 tech:	Technion - Israel Institute of Technology (IL)
62 tlavu:	Tel Aviv University (IR)
63 tsu:	Tsinghua University (CN)
64 tub:	Technical University of Berlin (DE)
65 tud:	Technical University of Darmstadt (DE)
66 tum:	Technical University of München (DE)
67 ucl:	University College London (UK)
68 ued:	University of Edinburgh (UK)
69 uiu:	University of Illinois at Urbana-Champaign (US)
70 unlu:	University of Luxembourg (LU)
71 unsw:	University of New South Wales (AU)
72 unt:	University of Toronto (CA)
73 uta:	University of Texas at Austin (US)
74 utj:	University of Tokyo (JP)
75 utw:	University of Twente (NL)
76 uwa:	University of Waterloo (CA)
77 wash:	University of Washington (US)
78 wtu:	Vienna University of Technology (AUS)
79 zhej:	Zhejiang University (CN)

The THE authors base their ranking decisions on five objectives.

```
1 >>> for obj in t.objectives:
2 ...     print('%s: %s (%.1f%%),\n\t%s' \
3 ...           % (obj,t.objectives[obj]['name'],
4 ...               t.objectives[obj]['weight'],
5 ...               t.objectives[obj]['comment'])
6 ...
7
8     Teaching: Best learning environment (30.0%),
9         Reputation survey; Staff-to-student ration;
10        Doctorate-to-student ratio,
11        Doctorate-to-academic-staff ratio, Institutional income.
12     Research: Highest volume and repustation (30.0%),
13         Reputation survey; Research income; Research productivity
14     Citations: Highest research influence (27.5%),
15         Impact.
16     International outlook: Most international staff, students and research
17     ↪(7.5%),
18         Proportions of international students; of international staff;
19         international collaborations.
20     Industry income: Best knowledge transfer (5.0%),
21         Volume.
```

With a cumulated importance of 87% (see above), *Teaching*, *Research* and *Citations* represent clearly the **major** ranking objectives. *International outlook* and *Industry income* are considered of **minor** importance (12.5%).

THE does, unfortunately, not publish the detail of their performance assessments for grading CS Depts with respect to each one of the five ranking objectives³⁹. The THE 2016 ranking publication reveals solely a compound assessment on a single *performance criteria* per ranking objective. The five retained performance criteria may be printed out as follows.

```
1 >>> for g in t.criteria:
2 ...     print('%s:\t%s, %s (%.1f%%)' \
3 ...           % (g,t.criteria[g]['name'],t.criteria[g]['comment'],
4 ...               t.criteria[g]['weight']) )
5
6     gtch:      Teaching, The learning environment (30.0%)
7     gres:      Research, Volume, income and reputation (30.0%)
8     gcit:      Citations, Research influence (27.5%)
9     gint:      International outlook, In staff, students and research (7.5
10    ↪%)
10     gind:      Industry income, knowledge transfer (5.0%)
```

³⁹ https://www.timeshighereducation.com/sites/default/files/styles/article785xauto/public/wur_graphic_1.jpg?itok=XS6NcZfL gives some insight on the subject and significance of the actual performance criteria used for grading along each ranking objective.

The largest part (87.5%) of criteria significance is, hence canonically, allocated to the major ranking criteria: *Teaching* (30%), *Research* (30%) and *Citations* (27.5%). The small remaining part (12.5%) goes to *International outlook* (7.5%) and *Industry income* (5%).

In order to render commensurable these performance criteria, the THE authors replace, per criterion, the actual performance grade obtained by each University with the corresponding **quantile** observed in the *cumulative distribution* of the performance grades obtained by all the surveyed institutions⁴⁰. The THE ranking is eventually determined by an **overall score** per University which corresponds to the **weighted average** of these five criteria quantiles (see Listing 3.12 below).

Listing 3.12: Computing the THE overall scores

```

1 >>> theScores = []
2 >>> for x in t.actions:
3 ...     xscore = Decimal('0')
4 ...     for g in t.criteria:
5 ...         xscore += t.evaluation[g][x] * \
6 ...             (t.criteria[g]['weight']/Decimal('100'))
7 ...     theScores.append((xscore,x))

```

In Listing 3.13 Lines 15-16 below, we may thus notice that, in the 2016 edition of the *THE World University rankings* by CS subject, the *Swiss Federal Institute of Technology Zürich* is first-ranked with an overall score of 92.9; followed by the *California Institute of Technology* (overall score: 92.4)³⁸.

Listing 3.13: Printing the ranked performance table

```

1 >>> theScores.sort(reverse = True)
2 >>> print('## Univ \tgtch gres gcit gint gind overall')
3 >>> print('-----')
4 >>> i = 1
5 >>> for it in theScores:
6 ...     x = it[1]
7 ...     xScore = it[0]
8 ...     print('%2d: %s' % (i,x), end=' \t')
9 ...     for g in t.criteria:
10 ...         print('%.1f' % (t.evaluation[g][x]), end=' ')
11 ...     print(' %.1f' % xScore)
12 ...     i += 1
13
14 ## Univ      gtch    gres    gcit    gint    gind    overall
15 -----
16 1: ethz      89.2   97.3   97.1   93.6   64.1   92.9
17 2: calt      91.5   96.0   99.8   59.1   85.9   92.4

```

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⁴⁰ <https://www.timeshighereducation.com/world-university-rankings/methodology-world-university-rankings-2016-2017>

³⁸ The author's own Computer Science Dept at the *University of Luxembourg* was ranked on position 63 with an overall score of 58.0.

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18	3: oxf	94.0	92.0	98.8	93.6	44.3	92.2
19	4: mit	87.3	95.4	99.4	73.9	87.5	92.1
20	5: git	87.2	99.7	91.3	63.0	79.5	89.9
21	6: cmel	88.1	92.3	99.4	58.9	71.1	89.4
22	7: icl	90.1	87.5	95.1	94.3	49.9	89.0
23	8: epfl	86.3	91.6	94.8	97.2	42.7	88.9
24	9: tum	87.6	95.1	87.9	52.9	95.1	87.7
25	10: sing	89.9	91.3	83.0	95.3	50.6	86.9
26	11: cou	81.6	94.1	99.7	55.7	45.7	86.6
27	12: ucl	85.5	90.3	87.6	94.7	42.4	86.1
28	13: wash	84.4	88.7	99.3	57.4	41.2	85.6
29	14: hkst	74.3	92.0	96.2	84.4	55.8	85.5
30	15: ntu	76.6	87.7	90.4	92.9	86.9	85.5
31	16: ued	85.7	85.3	89.7	95.0	38.8	85.0
32	17: unt	79.9	84.4	99.6	77.6	38.4	84.4
33	18: uiu	85.0	83.1	99.2	51.4	42.2	83.7
34	19: mcp	79.7	89.3	94.6	29.8	51.7	81.5
35	20: cbu	81.2	78.5	94.7	66.9	45.7	81.3
36	21: tsu	88.1	90.2	76.7	27.1	85.9	80.9
37	22: csd	75.2	81.6	99.8	39.7	59.8	80.5
38	23: uwa	75.3	82.6	91.3	72.9	41.5	80.0
39	24: nyu	71.1	77.4	99.4	78.0	39.8	79.7
40	25: uta	72.6	85.3	99.6	31.6	49.7	79.6
41	26: kit	73.8	85.5	84.4	41.3	76.8	77.9
42	27: bju	83.0	85.3	70.1	30.7	99.4	77.0
43	28: csb	65.6	70.9	94.8	72.9	74.9	76.2
44	29: rwth	77.8	85.0	70.8	43.7	89.4	76.1
45	30: hku	77.0	73.0	77.0	96.8	39.5	75.4
46	31: pud	76.9	84.8	70.8	58.1	56.7	75.2
47	32: kist	79.4	88.2	64.2	31.6	92.8	74.9
48	33: kcl	45.5	94.6	86.3	95.1	38.3	74.8
49	34: chku	64.1	69.3	94.7	75.6	49.9	74.2
50	35: epfr	81.7	60.6	78.1	85.3	62.9	73.7
51	36: dut	64.1	78.3	76.3	69.8	90.1	73.4
52	37: tub	66.2	82.4	71.0	55.4	99.9	73.3
53	38: utj	92.0	91.7	48.7	25.8	49.6	72.9
54	39: cir	68.8	64.6	93.0	65.1	40.4	72.5
55	40: ntw	81.5	79.8	66.6	25.5	67.6	72.0
56	41: anu	47.2	73.0	92.2	90.0	48.1	70.6
57	42: rcu	64.1	53.8	99.4	63.7	46.1	69.8
58	43: mel	56.1	70.2	83.7	83.3	50.4	69.7
59	44: lms	81.5	68.1	61.0	31.1	87.8	68.4
60	45: ens	71.8	40.9	98.7	69.6	43.5	68.3
61	46: wtu	61.8	73.5	73.7	51.9	62.2	67.9
62	47: tech	54.9	71.0	85.1	51.7	40.1	67.1
63	48: bro	58.5	54.9	96.8	52.3	38.6	66.5

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64	49: man	63.5	71.9	62.9	84.1	42.1	66.3
65	50: zhej	73.5	70.4	60.7	22.6	75.7	65.3
66	51: frei	54.2	51.6	89.5	49.7	99.9	65.1
67	52: unsw	60.2	58.2	70.5	87.0	44.3	63.6
68	53: kuj	75.4	72.8	49.5	28.3	51.4	62.8
69	54: sou	48.2	60.7	75.5	87.4	43.2	62.1
70	55: shJi	66.9	68.3	62.4	22.8	38.5	61.4
71	56: itmo	58.0	32.0	98.7	39.2	68.7	60.5
72	57: kul	35.2	55.8	92.0	46.0	88.3	60.5
73	58: glas	35.2	52.5	91.2	85.8	39.2	59.8
74	59: utw	38.2	52.8	87.0	69.0	60.0	59.4
75	60: stut	54.2	60.6	61.1	36.3	97.8	58.9
76	61: naji	51.4	76.9	48.8	39.7	74.4	58.6
77	62: tud	46.6	53.6	75.9	53.7	66.5	58.3
78	63: unlu	35.2	44.2	87.4	99.7	54.1	58.0
79	64: qut	45.5	42.6	82.8	75.2	63.0	58.0
80	65: hkpu	46.8	36.5	91.4	73.2	41.5	57.7
81	66: albt	39.2	53.3	69.9	91.9	75.4	57.6
82	67: mil	46.4	64.3	69.2	44.1	38.5	57.5
83	68: hels	48.8	49.6	80.4	50.6	39.5	57.4
84	69: cihk	42.4	44.9	80.1	76.2	67.9	57.3
85	70: tlavu	34.1	57.2	89.0	45.3	38.6	57.2
86	71: indis	56.9	76.1	49.3	20.1	41.5	57.0
87	72: ariz	28.4	61.8	84.3	59.3	42.0	56.8
88	73: kth	44.8	42.0	83.6	71.6	39.2	56.4
89	74: humb	48.4	31.3	94.7	41.5	45.5	55.3
90	75: eind	32.4	48.4	81.5	72.2	45.8	54.4

It is important to notice that a ranking by weighted average scores requires *commensurable ranking criteria of precise decimal significance* and on which a *precise decimal performance grading* is given. It is very unlikely that the THE 2016 performance assessments indeed verify these conditions. This tutorial shows how to relax these methodological requirements -precise commensurable criteria and numerical assessments- by following instead an epistemic bipolar-valued logic based ranking methodology.

Ranking with multiple incommensurable criteria of ordinal significance

Let us, first, have a critical look at the THE performance criteria.

```
>>> t.showHTMLCriteria(Sorted=False)
```

the_cs_2016: Family of Criteria

#	Identifier	Name	Comment	Weight	Scale			Thresholds (ax + b)		
					direction	min	max	indifference	preference	veto
1	gtch	Teaching	The learning environment	30.00	max	0.00	100.00	0.00x + 2.50	0.00x + 5.00	0.00x + 60.00
2	gres	Research	Volume, income and reputation	30.00	max	0.00	100.00	0.00x + 2.50	0.00x + 5.00	0.00x + 60.00
3	gcit	Citations	Research influence	27.50	max	0.00	100.00	0.00x + 2.50	0.00x + 5.00	0.00x + 60.00
4	gint	International outlook	In staff, students and research	7.50	max	0.00	100.00	0.00x + 2.50	0.00x + 5.00	
5	gind	Industry income	Innovation	5.00	max	0.00	100.00	0.00x + 2.50	0.00x + 5.00	

Fig. 3.8: The THE ranking criteria

Considering a very likely imprecision of the performance grading procedure, followed by some potential violation of uniform distributed quantile classes, we assume here that a performance quantile difference of up to **abs(2.5)%** is **insignificant**, whereas a difference of **abs(5)%** warrants a **clearly better**, resp. **clearly less good**, performance. With quantiles 94%, resp. 87.3%, *Oxford's CS* teaching environment, for instance, is thus clearly better evaluated than that of the *MIT* (see Listing 3.12 Lines 27-28). We shall furthermore assume that a **considerable** performance quantile difference of **abs(60)%**, observed on the three major ranking criteria: *Teaching*, *Research* and *Citations*, will trigger a **veto**, respectively a **counter-veto** against a *pairwise outranking*, respectively a *pairwise outranked* situation [BIS-2013].

The effect of these performance discrimination thresholds on the preference modelling may be inspected as follows.

Listing 3.14: Inspecting the performance discrimination thresholds

```

1  >>> t.showCriteria()
2  ----- criteria -----
3  gtch 'Teaching'
4      Scale = (Decimal('0.00'), Decimal('100.00'))
5      Weight = 0.300
6      Threshold ind : 2.50 + 0.00x ; percentile: 8.07
7      Threshold pref : 5.00 + 0.00x ; percentile: 15.75
8      Threshold veto : 60.00 + 0.00x ; percentile: 99.75
9  gres 'Research'
10     Scale = (Decimal('0.00'), Decimal('100.00'))
11     Weight = 0.300
12     Threshold ind : 2.50 + 0.00x ; percentile: 7.86
13     Threshold pref : 5.00 + 0.00x ; percentile: 16.14
14     Threshold veto : 60.00 + 0.00x ; percentile: 99.21
15  gcit 'Citations'
16      Scale = (Decimal('0.00'), Decimal('100.00'))
17      Weight = 0.275

```

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```

18 Threshold ind : 2.50 + 0.00x ; percentile: 11.82
19 Threshold pref : 5.00 + 0.00x ; percentile: 22.99
20 Threshold veto : 60.00 + 0.00x ; percentile: 100.00
21 gint 'International outlook'
22     Scale = (Decimal('0.00'), Decimal('100.00'))
23     Weight = 0.075
24     Threshold ind : 2.50 + 0.00x ; percentile: 6.45
25     Threshold pref : 5.00 + 0.00x ; percentile: 11.75
26 gind 'Industry income'
27     Scale = (Decimal('0.00'), Decimal('100.00'))
28     Weight = 0.050
29     Threshold ind : 2.50 + 0.00x ; percentile: 11.82
30     Threshold pref : 5.00 + 0.00x ; percentile: 21.51

```

Between 6% and 12% of the observed quantile differences are, thus, considered to be *insignificant*. Similarly, between 77% and 88% are considered to be *significant*. Less than 1% correspond to *considerable* quantile differences on both the *Teaching* and *Research* criteria; actually triggering an epistemic *polarisation* effect [BIS-2013].

Beside the likely imprecise performance discrimination, the **precise decimal** significance weights, as allocated by the THE authors to the five ranking criteria (see Fig. 3.8 Column *Weight*) are, as well, quite **questionable**. Significance weights may carry usually hidden strategies for rendering the performance evaluations commensurable in view of a numerical computation of the overall ranking scores. The eventual ranking result is thus as much depending on the precise values of the given criteria significance weights as, vice versa, the given precise significance weights are depending on the subjectively expected and accepted ranking results⁴². We will therefore drop such precise weights and, instead, only require a corresponding criteria significance preorder: $gtch = gres > gcit > gint > gind$. *Teaching environment* and *Research volume and reputation* are equally considered most important, followed by *Research influence*. Than comes *International outlook in staff, students and research* and, least important finally, *Industry income and innovation*.

Both these working hypotheses: performance *discrimination* thresholds and solely *ordinal* criteria significance, give us way to a ranking methodology based on **robust pairwise outranking** situations [BIS-2004b]:

- We say that CS Dept x **robustly outranks** CS Dept y when x positively outranks y with **all** significance weight vectors that are **compatible** with the *significance preorder*: $gtch = gres > gcit > gint > gind$;
- We say that CS Dept x is **robustly outranked** by CS Dept y when x is positively outranked by y with **all** significance weight vectors that are **compatible** with the *significance preorder*: $gtch = gres > gcit > gint > gind$;
- Otherwise, CS Depts x and y are considered to be **incomparable**.

A corresponding digraph constructor is provided by the `RobustOutrankingDigraph` class.

⁴² In a social choice context, this potential double bind between voting profiles and election result, corresponds to voting manipulation strategies.

Listing 3.15: Computing the robust outranking digraph

```

1 >>> from outrankingDigraphs import RobustOutrankingDigraph
2 >>> rdg = RobustOutrankingDigraph(t)
3 >>> rdg
4     ----- Object instance description -----
5 Instance class      : RobustOutrankingDigraph
6 Instance name        : robust_the_cs_2016
7 # Actions            : 75
8 # Criteria           : 5
9 Size                 : 2993
10 Determinateness (%) : 78.16
11 Valuation domain    : [-1.00;1.00]
12 >>> rdg.computeIncomparabilityDegree(Comments=True)
13 Incomparability degree (%) of digraph <robust_the_cs_2016>:
14     #links x<->y y: 2775, #incomparable: 102, #comparable: 2673
15     (#incomparable/#links) =  0.037
16 >>> rdg.computeTransitivityDegree(Comments=True)
17 Transitivity degree of digraph <robust_the_cs_2016>:
18     #triples x>y>z: 405150, #closed: 218489, #open: 186661
19     (#closed/#triples) =  0.539
20 >>> rdg.computeSymmetryDegree(Comments=True)
21 Symmetry degree (%) of digraph <robust_the_cs_2016>:
22     #arcs x>y: 2673, #symmetric: 320, #asymmetric: 2353
23     (#symmetric/#arcs) =  0.12

```

In the resulting digraph instance *rdg* (see Listing 3.15 Line 8), we observe 2993 such **robust pairwise outranking** situations validated with a mean significance of 78% (Line 9). Unfortunately, in our case here, they do not deliver any complete linear ranking relation. The robust outranking digraph *rdg* contains in fact 102 incomparability situations (3.7%, Line 13); nearly half of its transitive closure is missing (46.1%, Line 18) and 12% of the positive outranking situations correspond in fact to symmetric *indifference* situations (Line 22).

Worse even, the digraph *rdg* admits furthermore a high number of outranking circuits.

Listing 3.16: Inspecting outranking circuits

```

1 >>> rdg.computeChordlessCircuits()
2 >>> rdg.showChordlessCircuits()
3     ----- Chordless circuits -----
4 145 circuits.
5 1:  ['albt', 'unlu', 'ariz', 'hels'] , credibility : 0.300
6 2:  ['albt', 'tlavu', 'hels'] , credibility : 0.150
7 3:  ['anu', 'man', 'itmo'] , credibility : 0.250
8 4:  ['anu', 'zhej', 'rcu'] , credibility : 0.250
9 ...
10 ...

```

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```

11  82: ['csb', 'epfr', 'rwth'] , credibility : 0.250
12  83: ['csb', 'epfr', 'pud', 'nyu'] , credibility : 0.250
13  84: ['csd', 'kcl', 'kist'] , credibility : 0.250
14  ...
15  ...
16 142: ['kul', 'qut', 'mil'] , credibility : 0.250
17 143: ['lms', 'rcu', 'tech'] , credibility : 0.300
18 144: ['mil', 'stut', 'qut'] , credibility : 0.300
19 145: ['mil', 'stut', 'tud'] , credibility : 0.300

```

Among the 145 detected robust outranking circuits reported in Listing 3.16, we notice, for instance, two outranking circuits of length 4 (see circuits #1 and #83). Let us explore below the bipolar-valued robust outranking characteristics $r(x \succsim y)$ of the first circuit.

Listing 3.17: Showing the relation table with stability denotation

```

1 >>> rdg.showRelationTable(actionsSubset= ['albt', 'unlu', 'ariz', 'hels'],
2 ...                               Sorted=False)
3
4 * ---- Relation Table ----
5 r/(stab)|  'albt'  'unlu'  'ariz'  'hels'
6   -----|-----
7   'albt' |  +1.00  +0.30  +0.00  +0.00
8   |  (+4)  (+2)  (-1)  (-1)
9   'unlu' |  +0.00  +1.00  +0.40  +0.00
10  |  (+0)  (+4)  (+2)  (-1)
11  'ariz' |  +0.00  -0.12  +1.00  +0.40
12  |  (+1)  (-2)  (+4)  (+2)
13  'hels' |  +0.45  +0.00  -0.03  +1.00
14  |  (+2)  (+1)  (-2)  (+4)
15 Valuation domain: [-1.0; 1.0]
16 Stability denotation semantics:
17 +4|-4 : unanimous outranking | outranked situation;
18 +2|-2 : outranking | outranked situation validated
19           with all potential significance weights that are
20           compatible with the given significance preorder;
21 +1|-1 : validated outranking | outranked situation with
22           the given significance weights;
23 0    : indeterminate relational situation.

```

In Listing 3.17, we may notice that the robust outranking circuit ['albt', 'unlu', 'ariz', 'hels'] will reappear with all potential criteria significance weight vectors that are compatible with given preorder: $gtch = gres > gcit > gint > gind$. Notice also the $(+1|-1)$ marked outranking situations, like the one between 'albt' and 'ariz'. The statement that '*Arizona State University* strictly outranks *University of Alberta*' is in fact valid with the precise THE weight vector, but not with all potential weight vectors compatible with

the given significance preorder. All these outranking situations are hence put into **doubt** ($r(x \succsim y) = 0.00$) and the corresponding CS Depts, like *University of Alberta* and *Arizona State University*, become **incomparable** in a *robust outranking* sense.

Showing many incomparabilities and indifferences; not being transitive and containing many robust outranking circuits; all these relational characteristics, make that no ranking algorithm, applied to digraph rdg , does exist that would produce a *unique* optimal linear ranking result. Methodologically, we are only left with *ranking heuristics*. In the previous tutorial on *ranking with multiple criteria* (page 82) we have seen now several potential heuristic ranking rules that may be applied to rank from a pairwise outranking digraph; yet, delivering all potentially more or less diverging results. Considering the order of digraph rdg (75) and the largely unequal THE criteria significance weights, we rather opt, in this tutorial, for the *NetFlows ranking rule* (page 91)⁴¹. Its complexity in $O(n^2)$ is indeed quite tractable and, by avoiding potential *tyranny of short majority* effects, the *NetFlows* rule specifically takes the ranking criteria significance into a more fairly balanced account.

The *NetFlows* ranking result of the CS Depts may be computed explicitly as follows.

Listing 3.18: Computing the robust *NetFlows* ranking

```

1 >>> nfRanking = rdg.computeNetFlowsRanking()
2 >>> nfRanking
3 ['ethz', 'calt', 'mit', 'oxf', 'cmel', 'git', 'epfl',
4  'icl', 'cou', 'tum', 'wash', 'sing', 'hkst', 'ucl',
5  'uiu', 'unt', 'ued', 'ntu', 'mcp', 'csd', 'cbu',
6  'uta', 'tsu', 'nyu', 'uwa', 'csb', 'kit', 'utj',
7  'bju', 'kcl', 'chku', 'kist', 'rwth', 'pud', 'epfr',
8  'hku', 'rcu', 'cir', 'dut', 'ens', 'ntw', 'anu',
9  'tub', 'mel', 'lms', 'bro', 'frei', 'wtu', 'tech',
10 'itmo', 'zhej', 'man', 'kuj', 'kul', 'unsw', 'glas',
11 'utw', 'unlu', 'naji', 'sou', 'hkpu', 'qut', 'humb',
12 'shJi', 'stut', 'tud', 'tlavu', 'cihk', 'albt', 'indis',
13 'ariz', 'kth', 'hels', 'eind', 'mil']

```

We actually obtain a very similar ranking result as the one obtained with the THE overall scores. The same group of seven Depts: *ethz*, *calt*, *mit*, *oxf*, *cmel*, *git* and *epfl*, is top-ranked. And a same group of Depts: *tlavu*, *cihk*, *indis*, *ariz*, *kth*, *hels*, *eind*, and *mil* appears at the end of the list.

We may print out the difference between the *overall scores* based THE ranking and our *NetFlows* ranking with the following short Python script, where we make use of an ordered Python dictionary with *net flow scores*, stored in the *rdg.netFlowsRankingDict* attribute by the previous computation.

⁴¹ The reader might try other ranking rules, like *Copeland's*, *Kohler's*, *Tideman's* rule or the iterated versions of the *NetFlows* and *Copeland's* rule. Mind that the latter *ranking-by-choosing* rules are more complex.

Listing 3.19: Comparing the robust *NetFlows* ranking with the THE ranking

```

1  >>> # rdg.netFlowsRankingDict: ordered dictionary with net flow
2  >>> # scores stored in rdg by the computeNetFlowsRanking() method
3  >>> # theScores = [(xScore_1,x_1), (xScore_2,x_2),... ]
4  >>> # is sorted in decreasing order of xscores_i
5  >>> print(
6      ' NetFlows ranking    gtch   gres   gcit   gint   gind   THE ranking')
7
8  >>> for i in range(75):
9      x = nfRanking[i]
10     xScore = rdg.netFlowsRankingDict[x]['netFlow']
11     thexScore, thex = theScores[i]
12     print(' %2d: %s (%.2f) ' % (i+1, x, xScore), end=' \t')
13     for g in rdg.criteria:
14         print(' %.1f ' % (t.evaluation[g][x]), end=' ')
15     print(' %s (%.2f)' % (thex, thexScore) )
16
17
18     NetFlows ranking    gtch   gres   gcit   gint   gind   THE ranking
19     1: ethz (116.95)   89.2   97.3   97.1   93.6   64.1   ethz (92.88)
20     2: calt (116.15)   91.5   96.0   99.8   59.1   85.9   calt (92.42)
21     3: mit (112.72)   87.3   95.4   99.4   73.9   87.5   oxf (92.20)
22     4: oxf (112.00)   94.0   92.0   98.8   93.6   44.3   mit (92.06)
23     5: cmel (101.60)   88.1   92.3   99.4   58.9   71.1   git (89.88)
24     6: git (93.40)    87.2   99.7   91.3   63.0   79.5   cmel (89.43)
25     7: epfl (90.88)   86.3   91.6   94.8   97.2   42.7   icl (89.00)
26     8: icl (90.62)    90.1   87.5   95.1   94.3   49.9   epfl (88.86)
27     9: cou (84.60)    81.6   94.1   99.7   55.7   45.7   tum (87.70)
28    10: tum (80.42)    87.6   95.1   87.9   52.9   95.1   sing (86.86)
29    11: wash (76.28)   84.4   88.7   99.3   57.4   41.2   cou (86.59)
30    12: sing (73.05)   89.9   91.3   83.0   95.3   50.6   ucl (86.05)
31    13: hkst (71.05)   74.3   92.0   96.2   84.4   55.8   wash (85.60)
32    14: ucl (66.78)    85.5   90.3   87.6   94.7   42.4   hkst (85.47)
33    15: uiu (64.80)    85.0   83.1   99.2   51.4   42.2   ntu (85.46)
34    16: unt (62.65)    79.9   84.4   99.6   77.6   38.4   ued (85.03)
35    17: ued (58.67)    85.7   85.3   89.7   95.0   38.8   unt (84.42)
36    18: ntu (57.88)    76.6   87.7   90.4   92.9   86.9   uiu (83.67)
37    19: mcp (54.08)    79.7   89.3   94.6   29.8   51.7   mcp (81.53)
38    20: csd (46.62)    75.2   81.6   99.8   39.7   59.8   cbu (81.25)
39    21: cbu (44.27)    81.2   78.5   94.7   66.9   45.7   tsu (80.91)
40    22: uta (43.27)    72.6   85.3   99.6   31.6   49.7   csd (80.45)
41    23: tsu (42.42)    88.1   90.2   76.7   27.1   85.9   uwa (80.02)
42    24: nyu (35.30)    71.1   77.4   99.4   78.0   39.8   nyu (79.72)
43    25: uwa (28.88)    75.3   82.6   91.3   72.9   41.5   uta (79.61)
44    26: csb (18.18)    65.6   70.9   94.8   72.9   74.9   kit (77.94)
45    27: kit (16.32)    73.8   85.5   84.4   41.3   76.8   bju (77.04)

```

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45	28: utj (15.95)	92.0	91.7	48.7	25.8	49.6	csb (76.23)
46	29: bju (15.45)	83.0	85.3	70.1	30.7	99.4	rwth (76.06)
47	30: kcl (11.95)	45.5	94.6	86.3	95.1	38.3	hku (75.41)
48	31: chku (9.43)	64.1	69.3	94.7	75.6	49.9	pud (75.17)
49	32: kist (7.30)	79.4	88.2	64.2	31.6	92.8	kist (74.94)
50	33: rwth (5.00)	77.8	85.0	70.8	43.7	89.4	kcl (74.81)
51	34: pud (2.40)	76.9	84.8	70.8	58.1	56.7	chku (74.23)
52	35: epfr (-1.70)	81.7	60.6	78.1	85.3	62.9	epfr (73.71)
53	36: hku (-3.83)	77.0	73.0	77.0	96.8	39.5	dut (73.44)
54	37: rcu (-6.38)	64.1	53.8	99.4	63.7	46.1	tub (73.25)
55	38: cir (-8.20)	68.8	64.6	93.0	65.1	40.4	utj (72.92)
56	39: dut (-8.85)	64.1	78.3	76.3	69.8	90.1	cir (72.50)
57	40: ens (-8.97)	71.8	40.9	98.7	69.6	43.5	ntw (72.00)
58	41: ntw (-11.15)	81.5	79.8	66.6	25.5	67.6	anu (70.57)
59	42: anu (-11.50)	47.2	73.0	92.2	90.0	48.1	rcu (69.79)
60	43: tub (-12.20)	66.2	82.4	71.0	55.4	99.9	mel (69.67)
61	44: mel (-23.98)	56.1	70.2	83.7	83.3	50.4	lms (68.38)
62	45: lms (-25.43)	81.5	68.1	61.0	31.1	87.8	ens (68.35)
63	46: bro (-27.18)	58.5	54.9	96.8	52.3	38.6	wtu (67.86)
64	47: frei (-34.42)	54.2	51.6	89.5	49.7	99.9	tech (67.06)
65	48: wtu (-35.05)	61.8	73.5	73.7	51.9	62.2	bro (66.49)
66	49: tech (-37.95)	54.9	71.0	85.1	51.7	40.1	man (66.33)
67	50: itmo (-38.50)	58.0	32.0	98.7	39.2	68.7	zhej (65.34)
68	51: zhej (-43.70)	73.5	70.4	60.7	22.6	75.7	frei (65.08)
69	52: man (-44.83)	63.5	71.9	62.9	84.1	42.1	unsw (63.65)
70	53: kuj (-47.40)	75.4	72.8	49.5	28.3	51.4	kuj (62.77)
71	54: kul (-49.98)	35.2	55.8	92.0	46.0	88.3	sou (62.15)
72	55: unsw (-54.88)	60.2	58.2	70.5	87.0	44.3	shJi (61.35)
73	56: glas (-56.98)	35.2	52.5	91.2	85.8	39.2	itmo (60.52)
74	57: utw (-59.27)	38.2	52.8	87.0	69.0	60.0	kul (60.47)
75	58: unlu (-60.08)	35.2	44.2	87.4	99.7	54.1	glas (59.78)
76	59: naji (-60.52)	51.4	76.9	48.8	39.7	74.4	utw (59.40)
77	60: sou (-60.83)	48.2	60.7	75.5	87.4	43.2	stut (58.85)
78	61: hkpu (-62.05)	46.8	36.5	91.4	73.2	41.5	naji (58.61)
79	62: qut (-66.17)	45.5	42.6	82.8	75.2	63.0	tud (58.28)
80	63: humb (-68.10)	48.4	31.3	94.7	41.5	45.5	unlu (58.04)
81	64: shJi (-69.72)	66.9	68.3	62.4	22.8	38.5	qut (57.99)
82	65: stut (-69.90)	54.2	60.6	61.1	36.3	97.8	hkpu (57.69)
83	66: tud (-70.83)	46.6	53.6	75.9	53.7	66.5	albt (57.63)
84	67: tlavu (-71.50)	34.1	57.2	89.0	45.3	38.6	mil (57.47)
85	68: cihk (-72.20)	42.4	44.9	80.1	76.2	67.9	hels (57.40)
86	69: albt (-72.33)	39.2	53.3	69.9	91.9	75.4	cihk (57.33)
87	70: indis (-72.53)	56.9	76.1	49.3	20.1	41.5	tlavu (57.19)
88	71: ariz (-75.10)	28.4	61.8	84.3	59.3	42.0	indis (57.04)
89	72: kth (-77.10)	44.8	42.0	83.6	71.6	39.2	ariz (56.79)
90	73: hels (-79.55)	48.8	49.6	80.4	50.6	39.5	kth (56.36)

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91	74: eind (-82.85) 32.4 48.4 81.5 72.2 45.8 humb (55.34)
92	75: mil (-83.67) 46.4 64.3 69.2 44.1 38.5 eind (54.36)

The first inversion we observe in Listing 3.19 (Lines 20-21) concerns *Oxford University* and the *MIT*, switching positions 3 and 4. Most inversions are similarly short and concern only switching very close positions in either way. There are some slightly more important inversions concerning, for instance, the *Hong Kong University* CS Dept, ranked into position 30 in the THE ranking and here in the position 36 (Line 53). The opposite situation may also happen; the *Berlin Humboldt University* CS Dept, occupying the 74th position in the THE ranking, advances in the *NetFlows* ranking to position 63 (Line 80).

In our bipolar-valued epistemic framework, the *NetFlows* score of any CS Dept x (see Listing 3.19) corresponds to the criteria significance support for the logical statement (x is *first-ranked*). Formally

$$r(x \text{ is } \textit{first-ranked}) = \sum_{y \neq x} r((x \succsim y) + (y \not\succsim x)) = \sum_{y \neq x} (r(x \succsim y) - r(y \succsim x))$$

Using the robust outranking characteristics of digraph rdg , we may thus explicitly compute, for instance, *ETH Zürich*'s score, denoted nfx below.

```

1 >>> x = 'ethz'
2 >>> nfx = Decimal('0')
3 >>> for y in rdg.actions:
4 ...     if x != y:
5 ...         nfx += (rdg.relation[x][y] - rdg.relation[y][x])
6
7 >>> print(x, nfx)
8 ethz 116.950

```

In Listing 3.19 (Line 18), we may now verify that *ETH Zürich* obtains indeed the highest *NetFlows* score, and gives, hence the **most credible** *first-ranked* CS Dept of the 75 potential candidates.

How may we now convince the reader, that our pairwise outranking based ranking result here appears more objective and trustworthy, than the classic value theory based THE ranking by overall scores?

How to judge the quality of a ranking result?

In a multiple criteria based ranking problem, inspecting pairwise marginal performance differences may give objectivity to global preferential statements. That a CS Dept x convincingly outranks Dept y may thus conveniently be checked. The *ETH Zürich* CS Dept is, for instance, first ranked before *Caltech*'s Dept in both previous rankings. Lest us check the preferential reasons.

Listing 3.20: Comparing pairwise criteria performances

```

1 >>> rdg.showPairwiseOutrankings('ethz','calt')
2 *----- pairwise comparisons -----*
3 Valuation in range: -100.00 to +100.00
4 Comparing actions : (ethz, calt)
5 crit. wght. g(x) g(y) diff | ind pref r() |
6 -----
7 gcit 27.50 97.10 99.80 -2.70 | 2.50 5.00 +0.00 |
8 gind 5.00 64.10 85.90 -21.80 | 2.50 5.00 -5.00 |
9 gint 7.50 93.60 59.10 +34.50 | 2.50 5.00 +7.50 |
10 gres 30.00 97.30 96.00 +1.30 | 2.50 5.00 +30.00 |
11 gtch 30.00 89.20 91.50 -2.30 | 2.50 5.00 +30.00 |
12 r(x >= y): +62.50
13 crit. wght. g(y) g(x) diff | ind pref r() |
14 -----
15 gcit 27.50 99.80 97.10 +2.70 | 2.50 5.00 +27.50 |
16 gind 5.00 85.90 64.10 +21.80 | 2.50 5.00 +5.00 |
17 gint 7.50 59.10 93.60 -34.50 | 2.50 5.00 -7.50 |
18 gres 30.00 96.00 97.30 -1.30 | 2.50 5.00 +30.00 |
19 gtch 30.00 91.50 89.20 +2.30 | 2.50 5.00 +30.00 |
20 r(y >= x): +85.00

```

A significant positive performance difference (+34.50), concerning the *International outlook* criterion (of 7,5% significance), may be observed in favour of the *ETH Zürich* Dept (Line 9 above). Similarly, a significant positive performance difference (+21.80), concerning the *Industry income* criterion (of 5% significance), may be observed, this time, in favour of the *Caltech* Dept. The former, larger positive, performance difference, observed on a more significant criterion, gives so far a first convincing argument of 12.5% significance for putting *ETH Zürich* first, before *Caltech*. Yet, the slightly positive performance difference (+2.70) between *Caltech* and *ETH Zürich* on the *Citations* criterion (of 27.5% significance) confirms an *at least as good as* situation in favour of the *Caltech* Dept.

The inverse negative performance difference (-2.70), however, is neither *significant* (< -5.00), nor *insignificant* (> -2.50), and does hence **neither confirm nor infirm** a *not at least as good as* situation in disfavour of *ETH Zürich*. We observe here a convincing argument of 27.5% significance for putting *Caltech* first, before *ETH Zürich*.

Notice finally, that, on the *Teaching* and *Research* criteria of total significance 60%, both Depts do, with performance differences $< \text{abs}(2.50)$, one as well as the other. As these two major performance criteria necessarily support together always the highest significance with the imposed significance weight preorder: $gtch = gres > gcit > gint > gind$, both outranking situations get in fact globally confirmed at stability level +2 (see the advanced topic on stable outrankings with multiple criteria of ordinal significance).

We may well illustrate all such *stable outranking* situations with a browser view of the corresponding robust relation map using our *NetFlows* ranking.

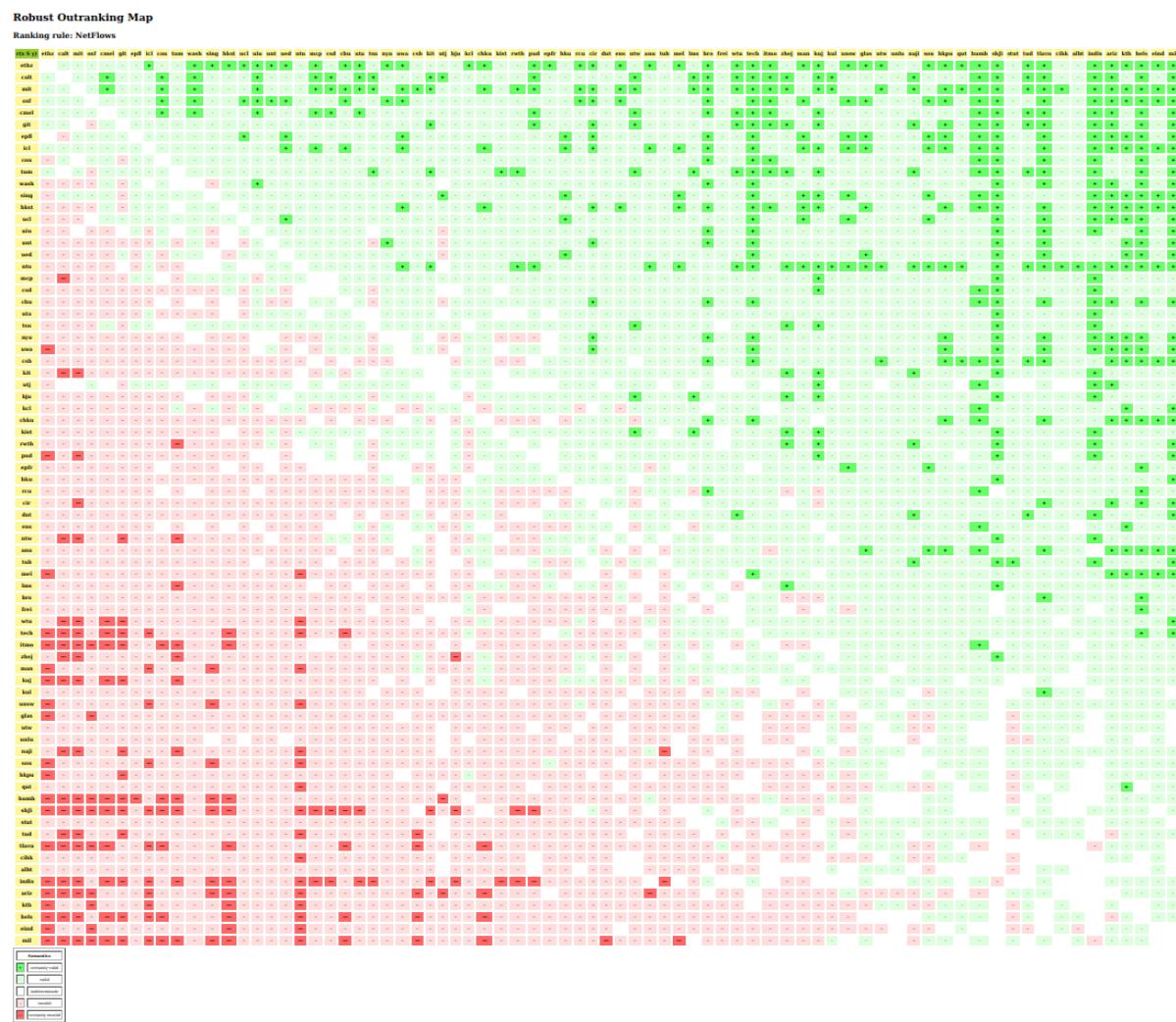


Fig. 3.9: Relation map of the robust outranking relation

In Fig. 3.9, **dark green**, resp. **light green** marked positions show *certainly*, resp. *positively* valid **outranking** situations, whereas **dark red**, resp. **light red** marked positions show *certainly*, respectively *positively* valid **outranked** situations. In the left upper corner we may verify that the five top-ranked Depts ([‘ethz’, ‘calt’, ‘oxf’, ‘mit’, ‘cmel’]) are indeed mutually outranking each other and thus are to be considered all *indifferent*. They are even robust *Condorcet* winners, i.e positively outranking all other Depts. We may by the way notice that no certainly valid outranking (dark green) and no certainly valid outranked situations (dark red) appear **below**, resp. **above** the principal diagonal; none of these are hence violated by our *netFlows* ranking.

The non reflexive **white** positions in the relation map, mark outranking or outranked situations that are **not robust** with respect to the given significance weight preorder. They are, hence, put into doubt and set to the *indeterminate* characteristic value **0**.

By measuring the **ordinal correlation** with the underlying pairwise *global* and *marginal*

robust outranking situations, the **quality** of the robust *netFlows* ranking result may be formally evaluated^{Page 188, 27}.

Listing 3.21: Measuring the quality of the *NetFlows* ranking result

```

1 >>> corrnf = rdg.computeRankingCorrelation(nfRanking)
2 >>> rdg.showCorrelation(corrnf)
3 Correlation indexes:
4   Crisp ordinal correlation : +0.901
5   Epistemic determination   : 0.563
6   Bipolar-valued equivalence : +0.507

```

In Listing 3.21 (Line 4), we may notice that the *NetFlows* ranking result is indeed highly ordinally correlated (+0.901, in *Kendall's* index *tau* sense) with the pairwise global robust outranking relation. Their bipolar-valued *relational equivalence* value (+0.51, Line 6) indicates a more than 75% criteria significance support.

We may as well check how the *netFlows* ranking rule is actually balancing the five ranking criteria.

```

1 >>> rdg.showRankingConsensusQuality(nfRanking)
2 Criterion (weight): correlation
3 -----
4   gtch (0.300): +0.660
5   gres (0.300): +0.638
6   gcit (0.275): +0.370
7   gint (0.075): +0.155
8   gind (0.050): +0.101
9 Summary:
10  Weighted mean marginal correlation (a): +0.508
11  Standard deviation (b)                 : +0.187
12  Ranking fairness (a)-(b)             : +0.321

```

The correlations with the marginal performance criterion rankings are nearly respecting the given significance weights preorder: $gtch \sim gres > gcit > gint > gind$ (see above Lines 4-8). The mean *marginal correlation* is quite high (+0.51). Coupled with a low standard deviation (0.187), we obtain a rather fairly balanced ranking result (Lines 10-12).

We may also inspect the mutual correlation indexes observed between the marginal criterion robust outranking relations.

```

1 >>> rdg.showCriteriaCorrelationTable()
2 Criteria ordinal correlation index
3   | gcit    gind    gint    gres    gtch
4   -----|-----
5   gcit | +1.00   -0.11   +0.24   +0.13   +0.17
6   gind |           +1.00   -0.18   +0.15   +0.15
7   gint |               +1.00   +0.04   -0.00

```

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8	gres	+1.00	+0.67
9	gtch		+1.00

Slightly contradictory (-0.11) appear the *Citations* and *Industrial income* criteria (Line 5 Column 3). Due perhaps to potential confidentiality clauses, it seems not always possible to publish industrially relevant research results in highly ranked journals. However, criteria *Citations* and *International outlook* show a slightly positive correlation (+0.24, Column 4), whereas the *International outlook* criterion shows no apparent correlation with both the major *Teaching* and *Research* criteria. The latter are however highly correlated (+0.67, Line 9 Column 6).

A *Principal Component Analysis* may well illustrate the previous findings.

```
>>> rdg.export3DplotOfCriteriaCorrelation(graphType='png')
```

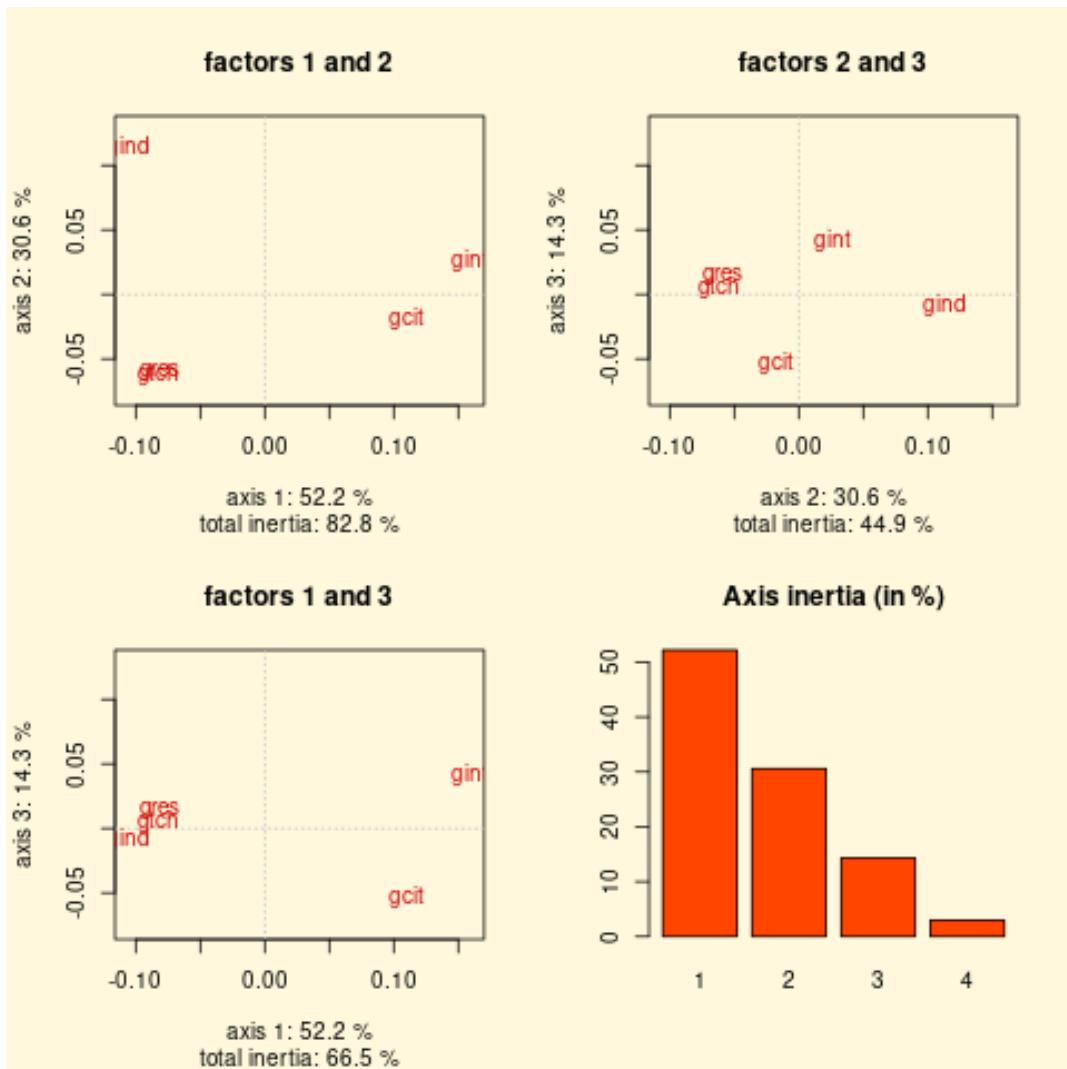


Fig. 3.10: 3D PCA plot of the pairwise criteria correlation table

In Fig. 3.10 (factors 1 and 2 plot) we may notice, first, that more than 80% of the total variance of the previous correlation table is explained by the apparent opposition

between the marginal outrankings of criteria: *Teaching, Research & Industry income* on the left side, and the marginal outrankings of criteria: *Citations & international outlook* on the right side. Notice also in the left lower corner the nearly identical positions of the marginal outrankings of the major *Teaching & Research* criteria. In the factors 2 and 3 plot, about 30% of the total variance is captured by the opposition between the marginal outrankings of the *Teaching & Research* criteria and the marginal outrankings of the *Industrial income* criterion. Finally, in the factors 1 and 3 plot, nearly 15% of the total variance is explained by the opposition between the marginal outrankings of the *International outlook* criterion and the marginal outrankings of the *Citations* criterion.

It may, finally, be interesting to assess, similarly, the ordinal correlation of the THE overall scores based ranking with respect to our robust outranking situations.

Listing 3.22: Computing the ordinal quality of the THE ranking

```

1  >>> # theScores = [(xScore_1,x_1), (xScore_2,x_2),... ]
2  >>> # is sorted in decreasing order of xscores
3  >>> theRanking = [item[1] for item in theScores]
4  >>> corrthe = rdg.computeRankingCorrelation(theRanking)
5  >>> rdg.showCorrelation(corrthe)
6  Correlation indexes:
7      Crisp ordinal correlation : +0.907
8      Epistemic determination   : 0.563
9      Bipolar-valued equivalence : +0.511
10 >>> rdg.showRankingConsensusQuality(theRanking)
11 Criterion (weight): correlation
12 -----
13     gtch (0.300): +0.683
14     gres (0.300): +0.670
15     gcit (0.275): +0.319
16     gint (0.075): +0.161
17     gind (0.050): +0.106
18 Summary:
19     Weighted mean marginal correlation (a): +0.511
20     Standard deviation (b)                 : +0.210
21     Ranking fairness (a)-(b)               : +0.302

```

The THE ranking result is similarly correlated (+0.907, Line 7) with the pairwise global robust outranking relation. By its overall weighted scoring rule, the THE ranking induces marginal criterion correlations that are naturally compatible with the given significance weight preorder (Lines 13-17). Notice that the mean marginal correlation is of a similar value (+0.51, Line 19) as the *netFlows* ranking's. Yet, its standard deviation is higher, which leads to a slightly less fair balancing of the three major ranking criteria.

To conclude, let us emphasize, that, without any commensurability hypothesis and by taking, furthermore, into account, first, the always present more or less imprecision of any performance grading and, secondly, solely ordinal criteria significance weights, we may obtain here with our robust outranking approach a very similar ranking result with more or less a same, when not better, preference modelling quality. A convincing heatmap

view of the 25 first-ranked Institutions may be generated in the default system browser with following command.

```
1 >>> rdg.showHTMLPerformanceHeatmap(  
2 ...     WithActionNames=True,  
3 ...     outrankingModel='this',  
4 ...     rankingRule='NetFlows',  
5 ...     ndigits=1,  
6 ...     Correlations=True,  
7 ...     fromIndex=0,toIndex=25)
```

Heatmap of Performance Tableau 'robust_the_cs_2016'

criteria	gtch	gres	gcit	gint	gind
weights	+30.00	+30.00	+27.50	+7.50	+5.00
tau(*)	+0.66	+0.64	+0.37	+0.15	+0.10
Swiss Federal Institute of Technology Zürich (ethz)	89.2	97.3	97.1	93.6	64.1
California Institute of Technology (calt)	91.5	96.0	99.8	59.1	85.9
Massachusetts Institute of Technology (mit)	87.3	95.4	99.4	73.9	87.5
University of Oxford (oxf)	94.0	92.0	98.8	93.6	44.3
Carnegie Mellon University (cmel)	88.1	92.3	99.4	58.9	71.1
Georgia Institute of Technology (git)	87.2	99.7	91.3	63.0	79.5
Swiss Federal Institute of Technology Lausanne (epfl)	86.3	91.6	94.8	97.2	42.7
Imperial College London (icl)	90.1	87.5	95.1	94.3	49.9
Cornell University (cou)	81.6	94.1	99.7	55.7	45.7
Technical University of München (tum)	87.6	95.1	87.9	52.9	95.1
University of Washington (wash)	84.4	88.7	99.3	57.4	41.2
National University of Singapore (sing)	89.9	91.3	83.0	95.3	50.6
Hong Kong University of Science and Technology (hkst)	74.3	92.0	96.2	84.4	55.8
University College London (ucl)	85.5	90.3	87.6	94.7	42.4
University of Illinois at Urbana-Champaign (uiu)	85.0	83.1	99.2	51.4	42.2
University of Toronto (unt)	79.9	84.4	99.6	77.6	38.4
University of Edinburgh (ued)	85.7	85.3	89.7	95.0	38.8
Nanyang Technological University of Singapore (ntu)	76.6	87.7	90.4	92.9	86.9
University of Maryland College Park (mcp)	79.7	89.3	94.6	29.8	51.7
University Of California at San Diego (csd)	75.2	81.6	99.8	39.7	59.8
Columbia University (cbu)	81.2	78.5	94.7	66.9	45.7
University of Texas at Austin (uta)	72.6	85.3	99.6	31.6	49.7
Tsinghua University (tsu)	88.1	90.2	76.7	27.1	85.9
New York University (nyu)	71.1	77.4	99.4	78.0	39.8
University of Waterloo (uwa)	75.3	82.6	91.3	72.9	41.5

Color legend:

quantile	14.29%	28.57%	42.86%	57.14%	71.43%	85.71%	100.00%
-----------------	--------	--------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation

Outranking model: **this**, Ranking rule: **NetFlows**

Ordinal (Kendall) correlation between global ranking and global outranking relation: **+0.901**

Mean marginal correlation (a) : **+0.508**

Standard marginal correlation deviation (b) : **+0.187**

Ranking fairness (a) - (b) : **+0.321**

Fig. 3.11: Extract of a heatmap browser view on the *NetFlows* ranking result

As an exercise, the reader is invited to try out other robust outranking based ranking heuristics. Notice also that we have not challenged in this tutorial the THE provided criteria significance preorder. It would be very interesting to consider the five ranking objectives as equally important and, consequently, consider the ranking criteria to be equisignificant. Curious to see the ranking results under such settings.

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3.3 The best students, where do they study? A *rating* case study

- *The performance tableau* (page 221)
- *Rating-by-ranking with lower-closed quantile limits* (page 225)
- *Inspecting the bipolar-valued outranking digraph* (page 230)
- *Rating by quantiles sorting* (page 231)
- *To conclude* (page 235)

In 2004, the German magazine *Der Spiegel*, with the help of *McKinsey & Company* and *AOL*, conducted an extensive online survey, assessing the apparent quality of German University students²⁸. More than 80,000 students, by participating, were questioned on their ‘Abitur’ and university exams’ marks, time of studies and age, grants, awards and publications, IT proficiency, linguistic skills, practical work experience, foreign mobility and civil engagement. Each student received in return a *quality score* through a specific weighing of the collected data which depended on the subject the student is mainly studying.²⁹.

The eventually published results by the *Spiegel* magazine concerned nearly 50,000 students, enroled in one of fifteen popular academic subjects, like *German Studies*, *Life Sciences*, *Psychology*, *Law* or *CS*. Publishing only those subject-University combinations, where at least 18 students had correctly filled in the questionnaire, left 41 German Universities where, for at least eight out of the fifteen subjects, an average enrolment quality score could be determined²⁹.

Based on this published data²⁸, we would like to present and discuss in this tutorial, how to **rate** the apparent global *enrolment quality* of these 41 higher education institutions with the help of our *Digraph3* software ressources.

The performance tableau

Published data of the 2004 *Spiegel* student survey is stored, for our evaluation purpose here, in a file named `studentenSpiegel04.py` of `PerformanceTableau` format³².

Listing 3.23: The 2004 Spiegel students survey data

```
1  >>> from perfTabs import PerformanceTableau
2  >>> t = PerformanceTableau('studentenSpiegel04')
3  >>> t
4  *----- PerformanceTableau instance description -----*
5  Instance class      : PerformanceTableau
```

(continues on next page)

²⁸ Ref: *Der Spiegel* 48/2004 p.181, Url: <https://www.spiegel.de/thema/studentenspiegel/>.

²⁹ The methodology guiding the *Spiegel* survey may be consulted in German [here](#). A copy may be consulted in *examples* directory of the *Digraph3* ressources.

³² The performance tableau `studentenSpiegel04.py` is also available in the `examples` directory of the *Digraph3* software collection.

(continued from previous page)

```
6 Instance name      : studentenSpiegel04
7 # Actions          : 41 (Universities)
8 # Criteria         : 15 (academic subjects)
9 NA proportion (%) : 27.3
10 Attributes        : ['name', 'actions', 'objectives',
11                           'criteria', 'weightPreorder',
12                           'evaluation']
13 >>> t.showHTMLPerformanceHeatmap(ndigits=1,
14                                     rankingRule=None)
... 
```

criteria	germ	pol	psy	soc	law	eco	mgt	bio	med	phys	chem	math	info	elec	mec
weights	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00
aach	53.3	50.8	62.7	51.0	NA	NA	49.6	52.2	49.5	59.1	53.6	58.6	54.6	57.2	54.4
aug	57.9	54.3	NA	54.8	45.6	NA	54.3	NA	NA	62.3	NA	61.2	58.1	NA	NA
berf	54.7	61.4	59.8	55.5	45.7	50.5	52.2	51.6	49.0	61.6	57.4	NA	54.9	NA	NA
berh	57.3	58.5	59.8	59.2	48.8	59.5	55.5	55.0	52.3	61.9	53.2	57.9	55.8	NA	NA
bertu	51.4	NA	57.7	59.1	NA	49.6	54.0	NA	NA	58.9	52.0	56.8	55.4	56.1	54.3
bie	51.4	NA	54.4	55.6	41.9	NA	50.7	49.7	NA	53.9	54.2	56.3	55.8	NA	NA
boc	53.9	NA	55.2	NA	39.1	NA	NA	48.0	49.8	56.8	53.3	57.6	NA	54.2	54.4
bon	54.1	57.3	60.3	56.0	47.2	53.6	NA	50.1	3.0	59.9	53.1	59.4	53.7	NA	NA
brau	53.5	54.0	NA	51.5	NA	NA	53.4	53.1	NA	59.8	50.1	54.7	52.6	54.5	55.2
brem	56.9	55.5	52.5	54.5	40.9	NA	55.4	53.3	NA	59.7	NA	NA	54.1	50.1	NA
chem	54.3	57.1	60.8	53.3	NA	NA	52.7	NA	NA	NA	NA	NA	57.7	57.5	53.6
darm	1.0	59.7	58.6	52.0	NA	NA	NA	1.0	NA	62.5	2.0	59.4	3.0	NA	56.1
dres	55.2	55.9	60.6	56.2	44.0	56.7	54.8	55.3	49.2	59.9	55.8	57.8	56.2	56.1	54.8
dsd	53.5	NA	57.5	48.8	44.9	NA	50.5	47.3	50.5	NA	53.5	NA	NA	NA	NA
duis	50.6	52.5	NA	47.9	NA	NA	47.5	NA	48.0	54.6	52.8	51.6	56.8	53.6	51.9
erl	57.9	55.1	58.7	55.4	42.9	NA	55.6	51.8	49.3	60.3	54.0	60.5	54.6	55.9	55.1
fran	51.7	53.1	58.0	51.5	41.9	53.5	52.0	51.3	51.2	62.1	55.5	57.0	52.4	NA	NA
frei	57.8	60.5	64.1	57.5	50.7	53.3	NA	55.4	54.2	61.6	57.0	60.6	58.1	NA	NA
gie	53.0	59.0	58.0	NA	41.9	NA	51.2	50.4	50.0	57.6	NA	NA	NA	NA	NA
goet	58.7	56.3	59.8	53.5	44.8	53.6	52.6	50.5	48.9	60.4	53.9	63.1	NA	NA	NA
ham	57.0	60.2	57.3	53.6	44.1	52.1	49.8	52.7	49.2	56.4	54.2	54.9	54.7	NA	NA
han	50.4	52.8	NA	49.9	41.2	NA	NA	53.8	NA	57.5	53.6	56.6	58.8	53.5	53.6
hei	61.4	59.5	59.8	52.2	51.1	54.4	NA	55.2	55.5	60.9	56.7	61.3	NA	NA	NA
jena	56.5	55.8	58.5	52.8	45.3	NA	56.2	52.7	51.1	61.6	57.8	NA	57.2	NA	NA
kiel	51.9	52.2	58.4	NA	45.1	50.5	52.8	52.7	49.6	59.7	52.8	NA	54.9	54.2	NA
koel	51.7	57.6	58.9	56.1	46.1	56.1	54.6	51.8	50.7	58.7	54.0	56.5	NA	NA	NA
kons	56.9	65.9	59.1	54.7	48.3	59.0	NA	55.7	NA	59.9	58.0	NA	59.7	NA	NA
ksl	NA	NA	NA	NA	NA	NA	55.9	50.8	NA	59.7	54.6	62.2	56.2	57.5	56.3
leip	57.4	60.4	62.4	59.5	46.3	NA	54.6	56.9	51.5	62.2	57.0	NA	3.0	NA	NA
main	54.2	57.9	56.9	55.7	46.5	50.7	53.1	50.0	49.2	60.8	56.3	54.7	NA	NA	NA
marb	53.6	54.7	57.6	59.8	40.3	NA	55.5	53.2	51.1	62.8	57.8	NA	55.6	NA	NA
mnh	52.2	57.2	61.1	55.0	45.0	57.0	59.7	NA	NA	NA	NA	NA	58.6	NA	NA
mnst	55.4	56.7	62.2	56.3	46.4	54.1	56.3	51.2	52.8	55.2	55.0	56.9	57.7	NA	NA
mu	57.2	60.1	60.9	54.0	47.3	55.8	57.5	50.4	52.6	62.0	58.1	59.6	57.1	NA	NA
reg	54.8	55.4	62.1	NA	46.1	52.3	55.5	54.6	50.9	60.5	55.8	59.2	NA	NA	NA
saar	57.9	NA	56.5	NA	48.1	NA	52.2	NA	49.6	61.2	56.2	NA	57.6	NA	NA
stu	52.5	58.4	NA	NA	NA	NA	56.6	57.1	NA	61.5	55.2	60.6	59.8	60.2	57.8
tri	54.1	58.0	58.3	54.9	46.3	52.8	52.8	NA	NA	60.7	52.3	NA	NA	NA	NA
tueb	57.9	57.7	58.4	1.0	46.8	60.8	54.4	53.7	52.1	61.6	57.5	NA	55.2	NA	NA
tum	NA	NA	NA	NA	NA	NA	68.0	53.6	60.1	62.8	58.8	62.6	58.2	58.2	56.9
wrzb	56.9	56.0	59.8	NA	46.4	53.3	52.8	53.0	52.2	60.2	56.6	NA	55.9	NA	NA

Color legend:

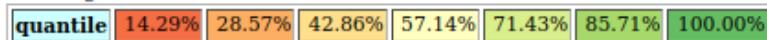


Fig. 3.12: Average quality of enroled students per academic subject

In Fig. 3.12, the fifteen popular academic subjects are grouped into topical ‘*Faculties*’:

- *Humanities*; - *Law, Economics & Management*; - *Life Sciences & Medicine*; - *Natural Sciences & Mathematics*; and - *Technology*. All fifteen subjects are considered *equally significant* for our evaluation problem (see Row 2). The recorded average enrolment quality scores appear coloured along a 7-tiling scheme per subject (see last Row).

We may by the way notice that *TU Dresden* is the only Institution showing enrolment quality scores in all the fifteen academic subjects. Whereas, on the one side, *TU München* and *Kaiserslautern* are only valued in *Sciences* and *Technology* subjects. On the other side, *Mannheim*, is only valued in *Humanities* and *Law, Economics & Management* studies. Most of the 41 Universities are not valued in *Engineering* studies. We are, hence, facing a large part (27.3%) of irreducible missing data (see Listing 3.23 Line 9 and the advanced topic on coping with missing data).

Details of the enrolment quality criteria (the academic subjects) may be consulted in a browser view (see Fig. 3.13 below).

```
>>> t.showHTMLCriteria()
```

#	Identifier	Name	Comment	Weight	Scale			Thresholds (ax + b)		
					direction	min	max	Indifference	preference	veto
1	bio	Life Sciences	Life Sciences & Medicine	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
2	chem	Chemistry	Natural Sciences & Mathematics	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
3	eco	Economics	Law, Economics & Management	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
4	elec	Electrical Engineering	Technology	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
5	germ	German Studies	Humanities	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
6	info	Computer Science	Technology	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
7	law	Law Studies	Law, Economics & Management	1.00	max	35.00	65.00	0.00x + 0.10	0.00x + 0.50	
8	math	Mathematics	Natural Sciences & Mathematics	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
9	mec	Mechanical Engineering	Technology	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
10	med	Medicine	Life Sciences & Medicine	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
11	mgt	Management	Law, Economics & Management	1.00	max	40.00	80.00	0.00x + 0.10	0.00x + 0.50	
12	phys	Physics	Natural Sciences & Mathematics	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	
13	pol	Politology	Humanities	1.00	max	50.00	70.00	0.00x + 0.10	0.00x + 0.50	
14	psy	Psychology	Humanities	1.00	max	50.00	70.00	0.00x + 0.10	0.00x + 0.50	
15	soc	Sociology	Humanities	1.00	max	45.00	65.00	0.00x + 0.10	0.00x + 0.50	

Fig. 3.13: Details of the rating criteria

The evaluation of the individual quality score for a participating student actually depends on his or her mainly enroled subject [Page 221, 29](#). The apparent quality measurement scales thus largely differ indeed from subject to subject (see Fig. 3.13), like *Law Studies* (35.0 - 65.0) and *Politology* (50.0 - 70.0). The recorded average enrolment quality scores, hence, are in fact **incommensurable** between the subjects.

To take furthermore into account a potential and very likely *imprecision* of the individual quality scores' computation, we shall assume that, for all subjects, an average enrolment quality score difference of **0.1** is **insignificant**, wheras a difference of **0.5** is sufficient to *positively* attest a **better** enrolment quality.

The apparent *incommensurability* and very likely *imprecision* of the recorded average enrolment quality scores, renders **meaningless** any global averaging over the subjects per University of the enrolment quality. We shall therefore, similarly to the methodological approach of the *Spiegel* authors [Page 221, 29](#), proceed with an **order statistics** based *rating-by-ranking* approach (see tutorial on *rating with learned quantile norms* (page 117)).

Rating-by-ranking with lower-closed quantile limits

The Spiegel authors opted indeed for a simple 3-tiling of the Universities per valued academic subject, followed by an average *Borda* scores based global ranking^{Page 221, 29}. Here, our **epistemic logic** based **outranking approach**, allows us, with adequate choices of *indifference* (0.1) and *preference* (0.5) discrimination thresholds, to estimate **lower-closed 9-tiles** of the enrolment quality scores per subject and rank conjointly, with the help of the *Copeland* ranking rule³⁴ applied to a corresponding *bipolar-valued outranking* digraph, the 41 Universities **and** the lower limits of the estimated 9-tiles limits.

We need therefore to, first, estimate, with the help of the `PerformanceQuantiles` constructor, the lowerclosed 9-tiling of the average enrolment quality scores per academic subject.

Listing 3.24: Computing 9-tiles of the enrolment quality scores per subject

```
1 >>> from performanceQuantiles import PerformanceQuantiles
2 >>> pq = PerformanceQuantiles(t,numberOfBins=9,LowerClosed=True)
3 >>> pq
4 *----- PerformanceQuantiles instance description -----*
5 Instance class      : PerformanceQuantiles
6 Instance name       : 9-tiled_performances
7 # Criteria          : 15
8 # Quantiles          : 9 (LowerClosed)
9 # History sizes     : {'germ': 39, 'pol': 34, 'psy': 34, 'soc': 32,
10                          'law': 32, 'eco': 21, 'mgt': 34,
11                          'bio': 34, 'med': 28,
12                          'phys': 37, 'chem': 35, 'math': 27,
13                          'info': 33, 'elec': 14, 'mec': 13, }
```

The *history sizes*, reported in Listing 3.24 above, indicate the number of Universities valued in each one of the popular fifteen subjects. *German Studies*, for instance, are valued for 39 out of 41 Universities, whereas *Electrical* and *Mechanical Engineering* are only valued for 14, respectively 13 Institutions. None of the fifteen subjects are valued in all the 41 Universities³⁰.

We may inspect the resulting 9-tiling limits in a browser view.

```
>>> pq.showHTMLLimitingQuantiles(Transposed=True,Sorted=False,
...                               ndigits=1,title='9-tiled quality score limits')
```

³⁴ See the tutorial on *ranking with incommensurable performance criteria* (page 82).

³⁰ It would have been much more accurate to estimate such quantile limits from the individual quality scores of all the nearly 50,000 surveyed students. But this data was not public.

9-tiled quality score limits

Sampling sizes between 13 and 39.

criterion	0.00	0.11	0.22	0.33	0.44	0.56	0.67	0.78	0.89	1.00
bio	45.0	49.9	50.5	51.4	52.3	53.0	53.5	54.8	55.5	57.1
chem	45.0	52.8	53.5	54.0	54.4	55.6	56.4	57.1	57.8	58.8
eco	49.6	50.6	52.2	53.3	53.5	53.9	55.8	56.8	59.3	60.8
elec	50.1	53.6	54.2	54.4	55.9	56.1	57.3	57.5	59.1	60.2
germ	45.0	51.5	52.4	53.5	54.1	55.1	56.9	57.3	57.9	61.4
info	45.0	52.5	54.6	54.9	55.7	56.2	57.2	58.0	58.7	59.8
law	39.1	41.6	43.0	44.9	45.4	46.1	46.4	47.2	48.5	51.1
math	51.6	54.9	56.6	57.0	57.9	59.4	60.5	60.7	62.2	63.1
mec	51.9	53.6	54.2	54.4	54.7	55.1	55.8	56.4	57.4	57.8
med	45.0	49.0	49.2	49.6	50.2	51.0	51.4	52.3	54.0	60.1
mgt	47.5	50.7	52.2	52.8	53.5	54.6	55.5	55.7	56.8	68.0
phys	53.9	56.9	58.9	59.7	60.0	60.7	61.6	61.8	62.3	62.8
pol	50.8	53.0	54.9	55.8	56.7	57.6	58.3	59.6	60.4	65.9
psy	52.5	56.8	57.7	58.3	58.6	59.7	59.8	60.8	62.2	64.1
soc	45.0	50.5	52.0	53.4	54.5	55.0	55.6	56.2	59.1	59.8

Fig. 3.14: 9-tiling quality score limits per academic subject

In Fig. 3.14, we see confirmed again the **incommensurability** between the subjects, we noticed already in the apparent enrolment quality scoring , especially between *Law Studies* (39.1 - 51.1) and *Politology* (50.5 - 65.9). Universities valued in *Law studies* but not in *Politology*, like the University of *Bielefeld*, would see their enrolment quality *unfairly weakened* when simply averaging the enrolment quality scores over valued subjects.

We add, now, these 9-tiling quality score limits to the enrolment quality records of the 41 Universities and rank all these records conjointly together with the help of the `LearnedQuantilesRatingDigraph` constructor and by using the *Copeland ranking rule* (page 86).

```
>>> from sortingDigraphs import LearnedQuantilesRatingDigraph
>>> lqr = LearnedQuantilesRatingDigraph(pq,t,
...                                         rankingRule='Copeland')
```

The resulting ranking of the 41 Universities including the lower-closed 9-tiling score limits may be nicely illustrated with the help of a corresponding heatmap view (see Fig. 3.15).

```
>>> lqr.showHTMLRatingHeatmap(colorLevels=7,Correlations=True,
...                             ndigits=1,rankingRule='Copeland')
```

Ranking rule: Copeland; Ranking correlation: 0.967

criteria	germ	chem	phys	mgt	law	bio	psy	pol	info	med	soc	math	eco	elec	mec
weights	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0
tau(*)	+0.51	+0.48	+0.47	+0.46	+0.40	+0.39	+0.38	+0.37	+0.33	+0.33	+0.29	+0.28	+0.20	+0.14	+0.12
[0.89 -]	37.9	57.8	62.3	56.8	46.5	55.5	62.2	60.4	58.7	54.0	59.1	62.2	59.3	59.1	37.4
tum	NA	56.8	62.6	68.0	NA	53.6	NA	NA	56.2	60.1	NA	62.6	NA	58.2	56.9
frei	57.8	57.0	61.6	NA	50.7	55.4	64.1	60.5	58.1	54.2	57.5	60.6	53.3	NA	NA
kons	56.9	56.0	59.9	NA	48.3	55.7	59.1	65.9	59.7	NA	54.7	NA	59.0	NA	NA
leip	57.4	57.0	62.2	54.6	46.3	56.9	62.4	60.4	3.0	51.5	59.5	NA	NA	NA	NA
mu	57.2	56.1	62.0	57.5	47.3	50.4	60.9	60.1	57.1	52.6	54.0	59.6	55.8	NA	NA
hei	61.4	56.7	60.9	NA	51.1	55.2	59.8	59.5	NA	55.5	52.2	61.3	54.4	NA	NA
[0.78 -]	37.3	57.1	61.6	55.7	47.2	54.8	60.8	59.6	58.0	52.3	56.2	60.7	56.8	57.5	36.4
stu	52.5	55.2	61.5	56.6	NA	57.1	NA	58.4	59.8	NA	NA	60.6	NA	60.2	57.8
berh	57.3	53.2	61.9	55.5	46.8	55.0	59.8	58.5	55.8	52.3	59.2	57.9	59.5	NA	NA
[0.67 -]	36.9	56.4	61.6	55.5	46.4	53.5	59.8	58.3	57.2	51.4	55.6	60.5	55.8	57.3	55.8
aug	57.9	NA	62.3	54.3	45.6	NA	NA	34.3	56.1	NA	54.8	61.2	NA	NA	NA
mnh	52.2	NA	NA	59.7	45.0	NA	61.1	57.2	58.6	NA	55.0	NA	57.0	NA	NA
tueb	57.9	57.5	61.6	54.4	46.8	53.7	58.4	37.7	55.2	52.1	1.0	NA	60.8	NA	NA
mast	55.4	55.0	55.2	56.3	46.4	51.2	62.2	56.7	57.7	52.6	56.3	56.9	54.1	NA	NA
jena	56.5	57.8	61.6	56.2	45.3	52.7	56.5	55.8	57.2	51.1	52.6	NA	NA	NA	NA
reg	54.8	55.8	60.5	55.5	46.1	54.6	62.1	55.4	NA	50.9	NA	59.2	52.3	NA	NA
saar	37.9	56.2	61.2	52.2	48.1	NA	56.5	NA	57.6	49.6	NA	NA	NA	NA	NA
[0.56 -]	35.1	55.6	60.7	54.6	46.1	53.0	59.7	37.6	56.2	51.0	55.0	59.4	53.9	56.1	35.1
wrzb	56.9	56.6	60.2	52.8	46.4	53.0	59.8	56.0	55.9	52.2	NA	NA	53.3	NA	NA
dres	55.2	55.8	59.9	54.8	44.0	55.3	60.6	55.9	56.2	49.2	56.2	57.6	56.7	56.1	54.8
ksl	NA	54.6	59.7	55.9	NA	50.8	NA	NA	56.2	NA	NA	62.2	NA	57.5	56.3
marb	53.6	57.8	62.8	55.5	40.3	53.2	57.6	54.7	55.6	51.1	59.8	NA	NA	NA	NA
berf	54.7	57.4	61.6	52.2	45.7	51.6	59.8	61.4	54.9	49.0	55.5	NA	50.5	NA	NA
chem	54.3	NA	NA	52.7	NA	NA	60.6	57.1	57.7	NA	53.3	NA	NA	57.5	53.6
koel	51.7	54.0	58.7	54.6	46.1	51.8	56.9	57.6	NA	50.7	56.1	56.5	56.1	NA	NA
erl	57.9	54.0	60.3	55.6	42.9	51.8	56.7	55.1	54.6	49.3	55.4	60.5	NA	55.9	55.1
tri	54.1	NA	NA	52.8	46.3	NA	58.3	58.0	52.3	NA	54.9	60.7	52.8	NA	NA
[0.44 -]	34.1	54.4	60.0	53.5	45.4	52.3	58.6	56.7	55.7	50.2	54.5	57.9	53.5	55.9	34.7
goet	56.7	53.9	60.4	52.6	44.6	50.5	59.8	56.3	NA	48.9	53.5	63.1	53.6	NA	NA
main	54.2	56.3	60.8	53.1	46.5	50.0	56.9	57.9	NA	49.2	55.7	54.7	50.7	NA	NA
bon	54.1	53.1	59.9	NA	47.2	50.1	60.3	57.3	53.7	3.0	56.0	59.4	53.6	NA	NA
brem	56.9	NA	59.7	55.4	40.9	53.3	52.5	55.5	54.1	NA	54.5	NA	NA	50.1	NA
[0.33 -]	33.5	54.0	59.7	52.8	44.9	51.4	58.3	55.8	54.9	49.6	53.4	57.0	53.3	54.4	34.4
fran	51.7	55.5	62.1	52.0	41.9	51.3	58.0	53.1	52.4	51.2	51.5	57.0	53.5	NA	NA
ham	57.0	54.2	56.4	49.8	44.1	52.7	57.3	60.2	54.7	49.2	53.6	54.9	52.1	NA	NA
kiel	51.9	52.8	59.7	52.8	45.1	52.7	56.4	52.2	54.9	49.6	NA	NA	50.5	54.2	NA
aach	53.3	53.6	59.1	49.6	NA	52.2	62.7	50.8	54.6	49.5	51.0	58.6	NA	57.2	54.4
bertu	51.4	52.0	58.9	54.0	NA	57.7	NA	55.4	NA	39.1	56.8	49.6	56.1	54.3	NA
brau	53.5	50.1	59.8	53.4	NA	53.1	NA	54.0	52.6	NA	51.5	54.7	NA	54.5	55.2
darm	1.0	2.0	62.5	NA	NA	1.0	58.6	39.7	3.0	NA	52.0	59.4	NA	NA	56.1
[0.22 -]	32.4	53.5	56.9	52.2	43.0	50.5	57.7	34.9	54.6	49.2	52.0	56.6	52.2	54.2	34.2
gie	53.0	NA	57.6	51.2	41.9	50.4	58.0	59.0	NA	50.0	NA	NA	NA	NA	NA
dsd	53.5	53.5	NA	50.5	44.9	47.3	57.5	NA	NA	50.5	46.8	NA	NA	NA	NA
bie	51.4	54.2	53.9	50.7	41.9	49.7	54.4	NA	55.8	NA	55.6	56.3	NA	NA	NA
boc	53.9	53.3	56.8	NA	39.1	48.0	55.2	NA	NA	49.8	NA	57.6	NA	54.2	54.4
han	50.4	53.6	57.5	NA	41.2	53.8	NA	52.8	56.8	NA	49.9	56.6	NA	53.5	53.6
[0.11 -]	51.5	52.8	56.9	50.7	41.6	49.9	56.8	53.0	52.5	49.0	50.5	54.9	50.6	53.6	53.0
duis	50.6	52.8	54.6	47.5	NA	NA	NA	52.5	56.8	48.0	47.9	51.6	NA	53.6	51.9
[0.00 -]	1.0	2.0	53.3	47.3	39.1	1.0	52.5	50.6	3.0	3.0	1.0	31.6	49.6	50.1	51.5

Color legend:

quantile	14.29%	28.57%	42.86%	57.14%	71.43%	85.71%	100.00%
----------	--------	--------	--------	--------	--------	--------	---------

(*) tau: Ordinal (Kendall) correlation between marginal criterion and global ranking relation.

Fig. 3.15: Heatmap view of the 9-tiles rating-by-ranking result

The *ordinal correlation* (+0.967)³⁵ of the *Copeland ranking* with the underlying bipolar-valued outranking digraph is very high (see Fig. 3.15 Row 1). Most correlated subjects with this *rating-by-ranking* result appear to be *German Studies* (+0.51), *Chemistry* (+0.48), *Management* (+0.47) and *Physics* (+0.46). Both *Electrical* (+0.07) and *Mechanical Engineering* (+0.05) are the less correlated subjects (see Row 3).

From the actual ranking position of the lower 9-tiling limits, we may now immediately deduce the 9-tile enrolment quality equivalence classes. No University reaches the highest 9-tile ([0.89 –]). In the lowest 9-tile ([0.00 – 0.11]) we find the University *Duisburg*. The complete rating result may be easily printed out as follows.

Listing 3.25: Rating the Universities into enrolment quality 9-tiles

```

1 >>> lqr.showQuantilesRating()
2 ----- Quantiles rating result -----
3 [0.89 - 1.00] []
4 [0.78 - 0.89[ ['tum', 'frei', 'kons', 'leip', 'mu', 'hei']
5 [0.67 - 0.78[ ['stu', 'berh']
6 [0.56 - 0.67[ ['aug', 'mnh', 'tueb', 'mnst', 'jena',
7             'reg', 'saar']
8 [0.44 - 0.56[ ['wrzb', 'dres', 'ksl', 'marb', 'berf',
9             'chem', 'koel', 'erl', 'tri']
10 [0.33 - 0.44[ ['goet', 'main', 'bon', 'brem']
11 [0.22 - 0.33[ ['fran', 'ham', 'kiel', 'aach',
12             'bertu', 'brau', 'darm']
13 [0.11 - 0.22[ ['gie', 'dsd', 'bie', 'boc', 'han']
14 [0.00 - 0.11[ ['duis']]
```

Following Universities: *TU München, Freiburg, Konstanz, Leipzig, München* as well as *Heidelberg*, appear best rated in the eighth 9-tile ([0.78 – 0.89[, see Listing 3.25 Line 4]). Lowest-rated in the first 9-tile, as mentioned before, appears University *Duisburg* (Line 14). Midfield, the fifth 9-tile ([0.44 – 0.56]), consists of the Universities *Würzburg, TU Dresden, Kaiserslautern, Marburg, FU Berlin, Chemnitz, Köln, Erlangen-Nürnberg* and *Trier* (Lines 8-9).

A corresponding *graphviz* drawing may well illustrate all these enrolment quality equivalence classes.

```

>>> lqr.exportRatingByRankingGraphViz(fileName='ratingResult',
...                                         graphSize='12,12')
----- exporting a dot file for GraphViz tools -----
Exporting to ratingResult.dot
dot -Grankdir=TB -Tpdf dot -o ratingResult.png
```

³⁵ See the advanced topic on the ordinal correlation of bipolar-valued digraphs.

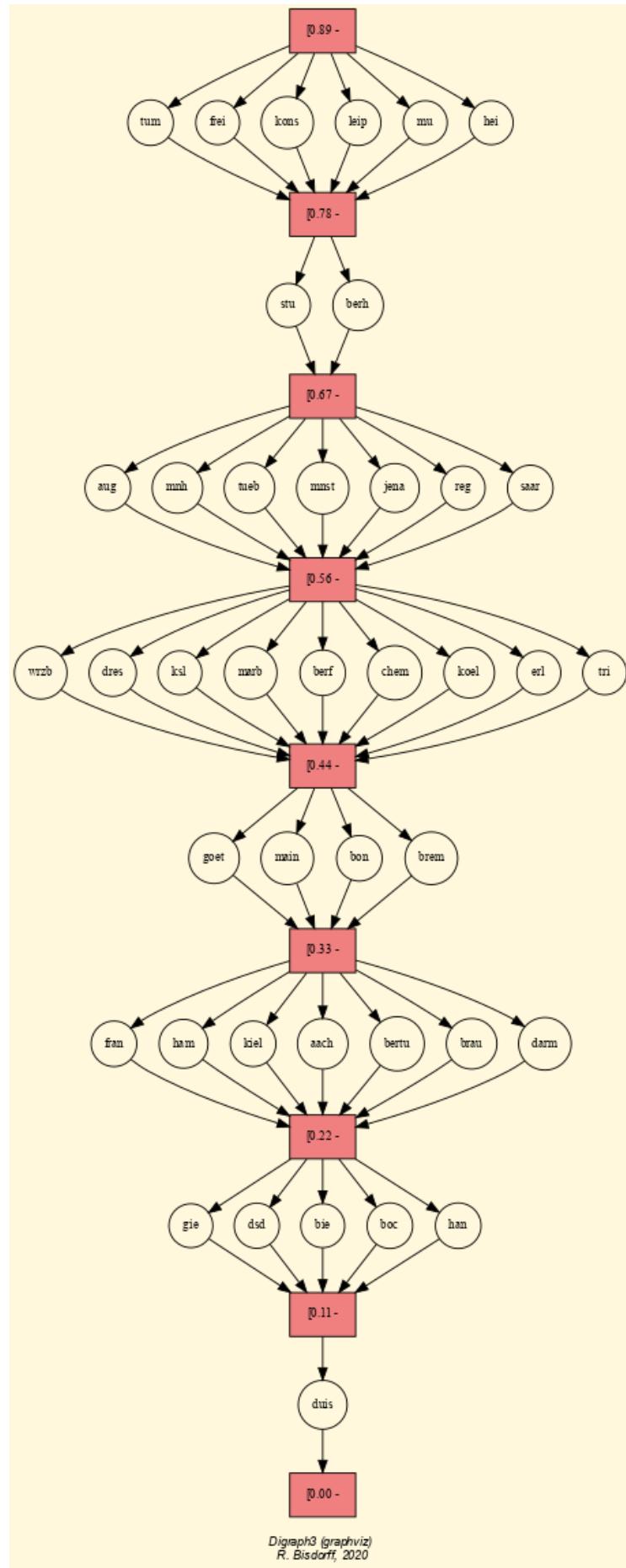


Fig. 3.16: Drawing of the 9-tiles rating-by-ranking result
229

We have noticed in the tutorial on *ranking with multiple criteria* (page 82), that there is not a single optimal rule for ranking from a given outranking digraph. The *Copeland* rule, for instance, has the advantage of being *Condorcet* consistent, i.e. when the outranking digraph models in fact a linear ranking, this ranking will necessarily be the result of the *Copeland* rule. When this is not the case, and especially when the outranking digraph shows many circuits, all potential ranking rules may give very divergent ranking results, and hence also substantially divergent rating-by-ranking results.

How *confident*, hence, is our precise *Copeland rating-by-ranking* result? To investigate this question, let us now inspect the **outranking digraph** on which we actually apply the *Copeland* ranking rule.

Inspecting the bipolar-valued outranking digraph

We say that University x **outranks** (resp. **is outranked by**) University y in enrolment quality when there exists a **majority** (resp. only a **minority**) of valuated subjects showing an **at least as good as** average enrolment quality score.

To compute these outranking situations, we use the `BipolarOutrankingDigraph` constructor.

Listing 3.26: Inspecting the bipolar-valued outranking digraph

```

1  >>> from outrankingDigraphs import BipolarOutrankingDigraph
2  >>> dg = BipolarOutrankingDigraph(t)
3  >>> dg
4  *----- Object instance description -----*
5  Instance class      : BipolarOutrankingDigraph
6  Instance name       : rel_studentenSpiegel04
7  # Actions           : 41 (Universities)
8  # Criteria          : 15 (subjects)
9  Size                : 828 (outranking situations)
10 Determinateness (%) : 63.67
11 Valuation domain   : [-1.00;1.00]
12 >>> dg.computeTransitivityDegree(Comments=True)
13 Transitivity degree of digraph <rel_studentenSpiegel04>:
14 #triples x>y>z: 57837, #closed: 30714, #open: 27123
15 (#closed/#triples) = 0.531
16 >>> dg.computeSymmetryDegree(Comments=True)
17 Symmetry degree of digraph <rel_studentenSpiegel04>:
18 #arcs x>y: 793, #symmetric: 35, #asymmetric: 758
19 #symmetric/#arcs = 0.044

```

The bipolar-valued outranking digraph dg (see Listing 3.23 Line 2), obtained with the given performance tableau t , shows 828 positively validated pairwise outranking situations (Line 9). Unfortunately, the transitivity of digraph dg is far from being satisfied: nearly half of the transitive closure is missing (Line 15). Despite the rather large *preference discrimination* threshold (0.5) we have assumed (see Fig. 3.13), there does not occur many indifference situations (Line 19).

We may furthermore check if there exists any *cyclic* outranking situations.

Listing 3.27: Enumerating chordless outranking circuits

```

1 >>> dg.computeChordlessCircuits()
2 >>> dg.showChordlessCircuits()
3     ----- Chordless circuits -----
4 93 circuits.
5 1: ['aach', 'bie', 'darm', 'brau'] , credibility : 0.067
6 2: ['aach', 'bertu', 'brau'] , credibility : 0.200
7 3: ['aach', 'bertu', 'brem'] , credibility : 0.067
8 4: ['aach', 'bertu', 'ham'] , credibility : 0.200
9 5: ['aug', 'tri', 'marb'] , credibility : 0.067
10 6: ['aug', 'jena', 'marb'] , credibility : 0.067
11 7: ['aug', 'jena', 'koel'] , credibility : 0.067
12 ...
13 ...
14 29: ['berh', 'kons', 'mu'] , credibility : 0.133
15 ...
16 ...
17 88: ['main', 'mnh', 'marb'] , credibility : 0.067
18 89: ['marb', 'saar', 'wrzb'] , credibility : 0.067
19 90: ['marb', 'saar', 'reg'] , credibility : 0.067
20 91: ['marb', 'saar', 'mnst'] , credibility : 0.133
21 92: ['marb', 'saar', 'tri'] , credibility : 0.067
22 93: ['mnh', 'mu', 'stu'] , credibility : 0.133

```

Here we observe indeed 93 such outranking circuits, like: *Berlin Humboldt > Konstanz > München > Berlin Humboldt* supported by a $(0.133 + 1.0)/2 = 56.7\%$ majority of subjects³¹ (see Listing 3.27 circuit 29 above). In the *Copeland* ranking result shown in Fig. 3.15, these Universities appear positioned respectively at ranks 10, 4 and 6. In the *NetFlows* ranking result they would appear respectively at ranks 10, 6 and 5, thus inverting the positions of *Konstanz* and *München*. The occurrence in digraph *dg* of so many outranking circuits makes thus *doubtful* any *forced* linear ranking, independently of the specific ranking rule we might have applied.

To effectively check the quality of our *Copeland rating-by-ranking* result, we shall now compute a direct **sorting into 9-tiles** of the enrolment quality scores, without using any outranking digraph based ranking rule.

Rating by quantiles sorting

In our case here, the Universities represent the decision actions: *where to study*. We say now that University x is sorted into the lower-closed 9-tile q when the performance record of x **positively outranks the lower limit** record of 9-tile q and x **does not positively outrank the upper limit** record of 9-tile q .

³¹ Converted by a +1.0 shift and a $0.5 * 100$ scale transform from a bipolar-valued credibility of +0.07 in [-1.0, +1.0] to a majority (in %) support.

Listing 3.28: Lower-closed 9-tiles sorting of the 41 Universities

```

1 >>> lqr.showActionsSortingResult()
2 Quantiles sorting result per decision action
3 [0.33 - 0.44[: aach with credibility: 0.13 = min(0.13,0.27)
4 [0.56 - 0.89[: aug with credibility: 0.13 = min(0.13,0.27)
5 [0.44 - 0.67[: berf with credibility: 0.13 = min(0.13,0.20)
6 [0.78 - 0.89[: berh with credibility: 0.13 = min(0.13,0.33)
7 [0.22 - 0.44[: bertu with credibility: 0.20 = min(0.33,0.20)
8 [0.11 - 0.22[: bie with credibility: 0.20 = min(0.33,0.20)
9 [0.22 - 0.33[: boc with credibility: 0.07 = min(0.07,0.07)
10 [0.44 - 0.56[: bon with credibility: 0.13 = min(0.20,0.13)
11 [0.33 - 0.44[: brau with credibility: 0.07 = min(0.07,0.27)
12 [0.33 - 0.44[: brem with credibility: 0.07 = min(0.07,0.07)
13 [0.44 - 0.56[: chem with credibility: 0.07 = min(0.13,0.07)
14 [0.22 - 0.56[: darm with credibility: 0.13 = min(0.13,0.13)
15 [0.56 - 0.67[: dres with credibility: 0.27 = min(0.27,0.47)
16 [0.22 - 0.33[: dsd with credibility: 0.07 = min(0.07,0.07)
17 [0.00 - 0.11[: duis with credibility: 0.33 = min(0.73,0.33)
18 [0.44 - 0.56[: erl with credibility: 0.13 = min(0.27,0.13)
19 [0.22 - 0.44[: fran with credibility: 0.13 = min(0.13,0.33)
20 [0.78 - <[: frei with credibility: 0.53 = min(0.53,1.00)
21 [0.22 - 0.33[: gie with credibility: 0.13 = min(0.13,0.20)
22 [0.33 - 0.44[: goet with credibility: 0.07 = min(0.47,0.07)
23 [0.22 - 0.33[: ham with credibility: 0.07 = min(0.33,0.07)
24 [0.11 - 0.22[: han with credibility: 0.20 = min(0.33,0.20)
25 [0.78 - 0.89[: hei with credibility: 0.13 = min(0.13,0.27)
26 [0.56 - 0.67[: jena with credibility: 0.07 = min(0.13,0.07)
27 [0.33 - 0.44[: kiel with credibility: 0.20 = min(0.20,0.47)
28 [0.44 - 0.56[: koel with credibility: 0.07 = min(0.27,0.07)
29 [0.78 - <[: kons with credibility: 0.20 = min(0.20,1.00)
30 [0.56 - 0.89[: ksl with credibility: 0.13 = min(0.13,0.40)
31 [0.78 - 0.89[: leip with credibility: 0.07 = min(0.20,0.07)
32 [0.44 - 0.56[: main with credibility: 0.07 = min(0.07,0.13)
33 [0.56 - 0.67[: marb with credibility: 0.07 = min(0.07,0.07)
34 [0.56 - 0.89[: mnh with credibility: 0.20 = min(0.20,0.27)
35 [0.56 - 0.67[: mnst with credibility: 0.07 = min(0.20,0.07)
36 [0.78 - 0.89[: mu with credibility: 0.13 = min(0.13,0.47)
37 [0.56 - 0.67[: reg with credibility: 0.20 = min(0.20,0.27)
38 [0.56 - 0.78[: saar with credibility: 0.13 = min(0.13,0.20)
39 [0.78 - 0.89[: stu with credibility: 0.07 = min(0.13,0.07)
40 [0.44 - 0.56[: tri with credibility: 0.07 = min(0.13,0.07)
41 [0.67 - 0.78[: tueb with credibility: 0.13 = min(0.13,0.20)
42 [0.89 - <[: tum with credibility: 0.13 = min(0.13,1.00)
43 [0.56 - 0.67[: wrzb with credibility: 0.07 = min(0.20,0.07)

```

In the 9-tiles sorting result, shown in Listing 3.28, we notice for instance in Lines 3-4 that the *RWTH Aachen* is precisely rated into the 4th 9-tile ($[0.33 - 0.44]$), whereas the University *Augsburg* is less precisely rated conjointly into the 6th, the 7th and the 8th 9-tile ($[0.56 - 0.89]$). In Line 42, *TU München* appears best rated into the unique highest 9-tile ($[0.89 - <]$). All three rating results are supported by a $(0.07 + 1.0)/2 = 53.5\%$ majority of valuated subjects^{Page 231, 31}. With the support of a 76.5% majority of valuated subjects (Line 20), the apparent most confident rating result is the one of University *Freiburg* (see also Fig. 3.12 and Fig. 3.15).

We shall now lexicographically sort these individual rating results per University, by *average* rated 9-tile limits and *highest-rated* upper 9-tile limit, into ordered, but not necessarily disjoint, enrolment quality quantiles.

```
>>> lqr.showHTMLQuantilesSorting(strategy='average')
```

quantile limits	Ordering by average quantile class limits
[0.89-<[['tum']
[0.78-<[['frei', 'kons']
[0.78-0.89[['berh', 'hei', 'leip', 'mu', 'stu']
[0.56-0.89[['aug', 'ksl', 'mnh']
[0.67-0.78[['tueb']
[0.56-0.78[['saar']
[0.56-0.67[['dres', 'jena', 'marb', 'mnst', 'reg', 'wrzb']
[0.44-0.67[['berf']
[0.44-0.56[['bon', 'chem', 'erl', 'koel', 'main', 'tri']
[0.22-0.56[['darm']
[0.33-0.44[['aach', 'brau', 'brem', 'goet', 'kiel']
[0.22-0.44[['bertu', 'fran']
[0.22-0.33[['boc', 'dsd', 'gie', 'ham']
[0.11-0.22[['bie', 'han']
[0.00-0.11[['duis']

Fig. 3.17: The ranked 9-tiles rating-by-sorting result

In Fig. 3.17 we may notice that the Universities: *Augsburg*, *Kaiserslautern*, *Mannheim* and *Tübingen* for instance, show in fact the same average rated 9-tiles score of 0.725; yet, the rated upper 9-tile limit of *Tuebingen* is only 0.78, whereas the one of the other Universities reaches 0.89. Hence, *Tuebingen* is ranked below *Augsburg*, *Kaiserslautern* and *Mannheim*.

With a special *graphviz* drawing of the `LearnedQuantilesRatingDigraph` instance *lqr*, we may, without requiring any specific ordering strategy, as well illustrate our 9-tiles *rating-by-sorting* result.

```
>>> lqr.exportRatingBySortingGraphViz(\n...     'nineTilingDrawing', graphSize='12,12')
```

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```
*----- exporting a dot file for GraphViz tools -----*
Exporting to nineTilingDrawing.dot
dot -Grankdir=TB -Tpng nineTilingDrawing.dot -o nineTilingDrawing.png
```

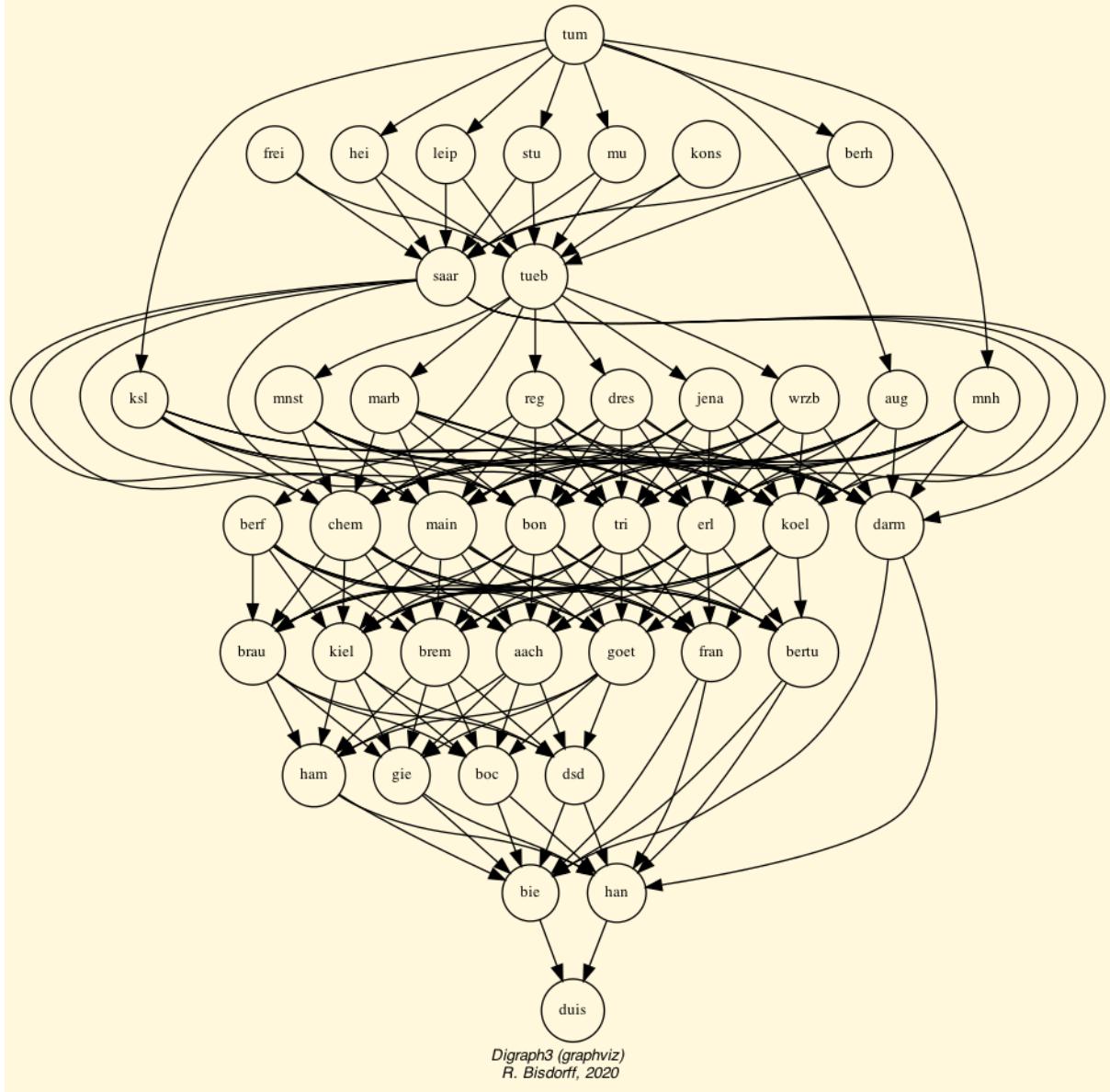


Fig. 3.18: Graphviz drawing of the 9-tiles sorting digraph

In Fig. 3.18 we actually see the *skeleton* (transitive closure removed) of a **partial order**, where an oriented arc is drawn between Universities x and y when their 9-tiles sorting results are **disjoint** and the one of x is **higher rated** than the one of y . The rating for *TU München* (see Listing 3.28 Lines 45), for instance, is disjoint and higher rated than the one of the Universities *Freiburg* and *Konstanz* (Lines 23, 32). And, both the ratings of *Feiburg* and *Konstanz* are, however, not disjoint from the one, for instance, of the University of *Stuttgart* (Line 42).

The partial ranking, shown in Fig. 3.18, is in fact **independent** of any ordering strategy:

- *average*, - *optimistic* or - *pessimistic*, of overlapping 9-tiles sorting results, and confirms that the same Universities as with the previous *rating-by-ranking* approach, namely *TU München, Freiburg, Konstanz, Stuttgart, Berlin Humboldt, Heidelberg* and *Leipzig* appear top-rated. Similarly, the Universities of *Duisburg, Bielefeld, Hanover, Bochum, Giessen, Düsseldorf* and *Hamburg* give the lowest-rated group. The midfield here is again consisting of more or less the same Universities as the one observed in the previous *rating-by-ranking* approach (see Fig. 3.16).

To conclude

In the end, both the *Copeland rating-by-ranking*, as well as the *rating-by-sorting* approach give luckily, in our case study here, very similar results. The first approach, with its *forced* linear ranking, determines on the one hand, *precise* enrolment quality equivalence classes; a result, depending potentially a lot on the actually applied ranking rule. The *rating-by-sorting* approach, on the other hand, only determines for each University a less precise but *prudent* rating of its individual enrolment quality, furthermore supported by a known majority of performance criteria significance; a somehow *fairer* and *robuster* result, but, much less evident for easily comparing the apparent enrolment quality among Universities. Contradictorily, or sparsely valued Universities, for instance, will appear trivially rated into a large midfield of adjacent 9-tiles.

Let us conclude by saying that we prefer this latter *rating-by-sorting* approach; perhaps impreciser, due the case given, to missing and contradictory performance data; yet, well grounded in a powerful bipolar-valued logical and epistemic framework (see the advanced topics of the Digraph3 documentation).

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3.4 Classmates matching: An *intragroup pairing* case study

- [A classmates matching problem](#) (page 235)
- [Computing a fair pairing solution](#) (page 237)
- [Using a fairness enhancing solver](#) (page 239)
- [Guiding the choice of the initial matching](#) (page 240)

A classmates matching problem

A class of ten university students has to be matched into partner pairs for a class activity. The students submitted the following approval-disapproval pairing preferences.

Student Ids	Pairing Approvals	Disapprovals
A (Alice)	C, F, I	B, G
B (Bob)	D, E, G	H, I, J
C (Carol))	A, F	B, G, I, J
D (Dan)	H	A, B, C
E (Edward)	B, D, F, H	A, C, G, I, J
F (Felix)	C, H, I	B, J
G (Gaby)	E, H	A, C, D
H (Henry)	D, F	B, E
I (Isabel)	A, C, G, J	B, D, E, F, H
J (Jane)	D, G	B, C, E

The given pairing preferences are gathered in a `BipolarApprovalVotingProfile` object stored under the name `classmates.py` in the `examples` directory of the `Digraph3` resources.

Listing 3.29: Example of intragroup pairing preferences

```

1  >>> from votingProfiles import BipolarApprovalVotingProfile
2  >>> bavp = BipolarApprovalVotingProfile('classmates')
3  >>> bavp.showBipolarApprovals()
4  Bipolar approval ballots
5  -----
6  A :
7  Approvals : ['C', 'F', 'I']
8  Disapprovals: ['B', 'G']
9  B :
10 Approvals : ['D', 'E', 'G']
11 Disapprovals: ['H', 'I', 'J']
12 C :
13 Approvals : ['A', 'F']
14 Disapprovals: ['B', 'G', 'I', 'J']
15 D :
16 Approvals : ['H']
17 Disapprovals: ['A', 'B', 'C']
18 E :
19 Approvals : ['B', 'D', 'F', 'H']
20 Disapprovals: ['A', 'C', 'G', 'I', 'J']
21 F :
22 Approvals : ['C', 'H', 'I']
23 Disapprovals: ['B', 'J']
24 G :
25 Approvals : ['E', 'H']
26 Disapprovals: ['A', 'C', 'D']
27 H :
28 Approvals : ['D', 'F']

```

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```
29 Disapprovals: ['B', 'E']
30 I :
31 Approvals : ['A', 'C', 'G', 'J']
32 Disapprovals: ['B', 'D', 'E', 'F', 'H']
33 J :
34 Approvals : ['D', 'G']
35 Disapprovals: ['B', 'C', 'E']
```

In Listing 3.29 we may notice that pairing *Alice* with *Carol* and *Bob* with *Edward* is evident as they both approve their reciprocal matches. *Gaby* however wants to be paired with *Edward* or *Henry*. Yet, both do not approve her as potential partner. Notice also that *Edward* wishes to be paired only with male partners and *Isabel* only with female ones. What is now a pairing solution which takes the fairest account of these individual approval and disapproval pairing preferences.

Computing a fair pairing solution

“**Fairness**: impartial and just treatment or behaviour without favouritism or discrimination” – Oxford Languages

The `pairings` module provides the `FairestIntraGroupPairing` constructor for computing by brute force over all $9!! = 945$ potential matchings the best ordinally correlated pairing solution with respect to the previously given `bavp` pairing approvals and disapprovals (see *tutorial on computing fair intragroup pairings* (page 171)).

Listing 3.30: Solving the intragroup pairing problem

```
1 >>> from pairings import FairestIntraGroupPairing
2 >>> fp = FairestIntraGroupPairing(bavp,orderLimit=10)
3 >>> fp
4 *----- IntraGroupPairing instance description -----*
5 Instance class      : FairestIntraGroupPairing
6 Instance name       : IntraGroupPairing
7 Group size          : 10
8 Nbr of matchings   : 945
9 Attributes          : ['name', 'persons', 'order', 'vpA',
10                      'nbrOfMatchings', 'pairings', 'matching',
11                      'avgCorr', 'stdCorr', 'groupScores',
12                      'runTimes', 'vertices', 'valuationDomain',
13                      'edges', 'gamma']
14 ---- Constructor run times (in sec.) ----
15 Total time          : 4.04574
16 Data input          : 0.00001
17 Maximal matchings  : 0.10362
18 Pairing correlations: 3.94153
19 Sorting Fitness     : 0.00052
20 Storing results     : 0.00006
```

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```
21 >>> fp.showMatchingFairness()
22 Matched pairs
23 {'A', 'I'}
24 {'B', 'E'}
25 {'C', 'F'}
26 {'G', 'J'}
27 {'H', 'D'}
28 -----
29 Individual correlations:
30 'A': +1.000
31 'B': +1.000
32 'C': +1.000
33 'D': +1.000
34 'E': +1.000
35 'F': +1.000
36 'G': +0.200
37 'H': +1.000
38 'I': +1.000
39 'J': +1.000
40 -----
41 Average correlation : +0.920
42 Standard deviation : 0.253
```

Looking in Listing 3.30 at the fairest pairing solution, we are lucky here as the pairing result is highly correlated with the pairing preferences of the ten classmates (+0.920, see Line 41). All students, except *Gaby*, are in fact paired with an approved partner and no student is paired with a disapproved partner. We may illustrate in Fig. 3.19 the resulting fairest intragroup pairing solution with a graphviz drawing.

```
>>> fp.exportGraphViz('fairestIntraGroupPairing2')
----- exporting a dot file for GraphViz tools -----
Exporting to fairestIntraGroupPairing2.dot
fdp -Tpng fairestIntraGroupPairing2.dot -o fairestIntraGroupPairing2.png
```

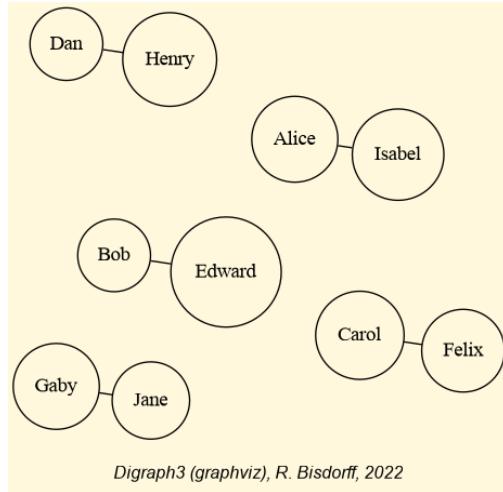


Fig. 3.19: Fairest intragroup pairing solution

Notice that with such a tiny group, the brute force solving approach –testing all 945 potential matchings– takes only about four seconds (see Line 15 in Listing 3.30). We may nevertheless try to reduce this solving runtime figure by using a smart fairness enhancing solver.

Using a fairness enhancing solver

The `FairnessEnhancedIntraGroupMatching` constructor, provided by the `pairings` module, may indeed reduce significantly the brute force solving run time, an essential feature when having to match larger groups of persons or items into pairs.

Listing 3.31: Fairness enhanced solving of the matching problem

```

1  >>> from pairings import FairnessEnhancedIntraGroupMatching
2  >>> fep = FairnessEnhancedIntraGroupMatching(bavp, Comments=True)
3  ====>>> Enhancing left initial matching
4  Initial left matching
5  [[['A', 'B'], ['C', 'D'], ['E', 'F'], ['G', 'H'], ['I', 'J']]]
6  Fairness enhanced left matching
7  [[['A', 'C'], ['B', 'G'], ['E', 'D'], ['F', 'H'], ['I', 'J']]]
8  correlation: 0.790
9  ====>>> Enhancing right initial matching
10 Initial right matching
11 [[['J', 'A'], ['I', 'B'], ['H', 'C'], ['G', 'D'], ['F', 'E']]]
12 Fairness enhanced right matching
13 [[['A', 'I'], ['C', 'F'], ['E', 'B'], ['G', 'J'], ['D', 'H']]]
14 correlation: 0.920
15 ====>>> Best fairness enhanced matching
16 Matched pairs
17 {'A', 'I'}
18 {'C', 'F'}
```

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```

19   {'D', 'H'}
20   {'E', 'B'}
21   {'G', 'J'}
22 Average correlation: +0.920
23 Total run time: 0.188 sec.

```

In Listing 3.31 above we may notice that the fairness enhancing procedure starts by default from two initial matchings, a right one and a left one (see Lines 5 and 11). Starting from each initial matching, the solver tries to swap either the two exterior persons $p_1 \leftrightarrow p_4$ and/or the interior persons $p_2 \leftrightarrow p_3$ of two potential student pairs $[[p_1, p_2], [p_3, p_4]]$ in order to enhance the fairness of the so far obtained pairing solution. Starting from the right initial matching, we recover here the same optimal fairest pairing result as before in a solving run time of less than one fifth of a second (see Line 23).

Guiding the choice of the initial matching

Instead of starting now from the default initial right and left matchings, we may also start in Listing 3.32 below the fairness enhancing search from a best *Copeland* matching, i.e. an initial matching where each student is paired with a partner who shows the highest possible matching fitness score with respect to the given individual student's pairing preferences⁶⁷.

Listing 3.32: Matching fitness scores

```

1 >>> from pairings import BestCopelandIntraGroupMatching
2 >>> bcm = BestCopelandIntraGroupMatching(bavp)
3 >>> bcm.showMatchingFitnessScores()
4      | 'B' 'C' 'D' 'E' 'F' 'G' 'H' 'I' 'J'
5      | -----
6 'A' | -16 +30 -16 -12 +12 -30 -2 +26 +0
7 'B' |      -12 +0 +26 -16 +16 -30 -24 -28
8 'C' |          -10 -6 +30 -26 +4 +0 -26
9 'D' |              +16 +2 -10 +34 -6 +20
10 'E' |                  +10 +6 -4 -20 -24
11 'F' |                      +0 +30 +4 -14
12 'G' |                          +16 +14 +18
13 'H' |                              -10 +2
14 'I' |                                  +14
15 Valuation domain: [-34, 34]

```

The pairwise matching fitness scores shown above in Lines 6-14 result from the sum of the *Copeland* ranking scores of the respective potential partners of both the paired persons. The fitness figures confirm for instance that the best matching fitness score of 34 is shown for pairing *Dan* and *Henry* (Line 9) followed by the best matching fitness score of 30 for pairing *Alice* is *Carol* (Line 6). A best matching fitness score of +26 than

⁶⁷ The `FairnessEnhancedIntraGroupMatching` class provides also the opportunity to use *Bachet* ranking scores instead of the *Copeland* scores for guiding the fairness enhancing procedure. Unfortunately, ongoing tests don't show any convincing better results.

appears for pairing *Bob* with **Edward* (Line 7). *Gaby* and *Jane* show a best matching fitness score of +18 (Line 12). Finally we are only left with *Felix* and *Isabel*. *Felix* approves *Isabel* but *Isabel* does only approve female partners; their reciprocal matching fitness score is eventually only +4 (Line 11)). Below is shown the resulting best fitting *Copeland* matching⁶⁶.

```
>>> bcm.matching
{ {'D', 'H'}, {'A', 'C'}, {'B', 'E'}, {'G', 'J'}, {'F', 'I'} }
```

Starting from this initial matching, we may now reach indeed the fairest possible pairing solution within one fairness enhancing step by exchanging *Alice* with *Felix*.

```
1  >>> fec = FairnessEnhancedIntraGroupMatching(bavp,
2      ...           initialMatching=bcm.matching)
3  >>> fec.showMatchingFairness()
4  Matched pairs
5  {'B', 'E'}
6  {'C', 'F'}
7  {'D', 'H'}
8  {'I', 'A'}
9  {'J', 'G'}
10 -----
11 Individual correlations:
12 'A': +1.000
13 'B': +1.000
14 'C': +1.000
15 'D': +1.000
16 'E': +1.000
17 'F': +1.000
18 'G': +0.200
19 'H': +1.000
20 'I': +1.000
21 'J': +1.000
22 -----
23 Average correlation : +0.920
24 Standard deviation   :  0.253
25 Total run time       :  0.075 sec.
```

Total solver run time is now reduced to less than a 13th of a second (0.075, see Line 23 above). The initial brute force solving run time of about 4.0 seconds is thus eventually divided by more than $4.0/0.075 \approx 53$ (see Listing 3.30 Line 16). With a polynomial run time for computing a best *Copeland* initial matching, intragroup pairing problems of larger group sizes become so effectively solvable.

⁶⁶ The best *Copeland* initial matching is computed following a matching fitness scores ranked potential pairs list.

See also

The tutorial on computing fair intragroup pairings (page 171).

Back to *Content Table* (page 1)

3.5 Fairest internship matching: An *intergroup pairing* case study

- *A graduate internship matching problem* (page 242)
- *Computing a fair matching* (page 243)
- *Using a fairness enhancing heuristic* (page 245)
- *Using bipolar approval-disapproval voting profiles* (page 247)

A graduate internship matching problem

A class of ten graduate students in their final medical science study year has to be matched with a set of ten internships offered by different organizations. The students submitted their individual preferences concerning the offered internships in the format of the following linear votings.

Student Ids	Matching Preferences
‘s01’	[i07, i09, i10, i08, i06, i04, i01, i05, i02, i03]
‘s02’	[i05, i09, i03, i07, i06, i10, i01, i08, i02, i04]
‘s03’	[i08, i09, i07, i10, i06, i01, i03, i02, i04, i05]
‘s04’	[i08, i03, i09, i02, i05, i01, i06, i10, i04, i07]
‘s05’	[i03, i01, i05, i10, i07, i08, i02, i06, i04, i09]
‘s06’	[i04, i10, i05, i01, i03, i06, i08, i02, i09, i07]
‘s07’	[i01, i02, i06, i08, i05, i10, i03, i04, i07, i09]
‘s08’	[i07, i09, i03, i05, i04, i06, i02, i08, i01, i10]
‘s09’	[i03, i02, i08, i07, i05, i04, i01, i10, i09, i06]
‘s10’	[i02, i10, i05, i07, i03, i09, i04, i01, i08, i06]

Students *s01* and *s08*, for instance, both mostly prefer internship *i07*, whereas students *s03* and *s04* both mostly prefer internship *i08*.

The organizations offering the internship opportunities submitted likewise their reciprocal preferences in the format of the following linear votings.

Internship Ids	Matching Preferences
'i01'	[s06, s10, s04, s05, s07, s08, s03, s09, s02, s01]
'i02'	[s09, s02, s05, s08, s07, s06, s04, s03, s01, s10]
'i03'	[s06, s10, s02, s04, s03, s08, s07, s01, s05, s09]
'i04'	[s04, s08, s01, s10, s06, s02, s05, s03, s09, s07]
'i05'	[s01, s10, s04, s02, s08, s07, s05, s09, s03, s06]
'i06'	[s01, s05, s07, s08, s02, s04, s03, s10, s06, s09]
'i07'	[s01, s02, s06, s07, s05, s10, s03, s08, s04, s09]
'i08'	[s05, s01, s07, s03, s02, s09, s04, s10, s06, s08]
'i09'	[s06, s01, s02, s04, s09, s07, s03, s08, s05, s10]
'i10'	[s02, s07, s04, s03, s01, s05, s10, s06, s09, s08]

The organizations offering for instance internships *i05*, *i06* and *i07* mostly prefer the same student *s01*, whereas the organizations offering internships *i01*, *i03* and *i09* mostly prefer student *s06*. These matching preferences are stored in the format of two reciprocal `LinearVotingProfile` objects stored under the names `lvpStudents.py` and `lvpInternships.py` in the `examples` directory of the Digraph3 resources.

How to compute now a matching of students and internships that takes fair account of these reciprocal matching preferences? A fair pairing solution should show a high average overall correlation index with the given reciprocal linear voting profiles and an as small as possible difference between the average correlations of the students and of the internships matching preferences

Computing a fair matching

Traditionally, such intergroup pairing problems are solved by using variants of the *deferred acceptance* algorithm like the *Gale-Shapley* or the *Roth-Peranson* algorithms⁶⁸. The `pairings` module provides for this purpose the `FairestGaleShapleyMatching` constructor computing both *Gale-Shapley* matchings – the students propose as well as the internships propose – and rendering the fairest solution of both (see tutorial on *computing fair intergroup pairings* (page 141)).

Listing 3.33: Fairest Gale-Shapley Matching

```

1 >>> from votingProfiles import LinearVotingProfile
2 >>> lvpS = LinearVotingProfile('lvpStudents')
3 >>> lvpI = LinearVotingProfile('lvpInternships')
4 >>> from pairings import FairestGaleShapleyMatching
5 >>> gsm = FairestGaleShapleyMatching(lvpS,lvpI)
6 >>> gsm.matching
7   [['s01', 'i07'], ['s02', 'i09'], ['s03', 'i10'], ['s04', 'i03'], ['s05',
8     'i08'],
8   ['s06', 'i01'], ['s07', 'i06'], ['s08', 'i04'], ['s09', 'i02'], ['s10',
8     'i05']]
```

⁶⁸ See https://en.wikipedia.org/wiki/Gale%20-%20Shapley_algorithm

In Listing 3.33 above we may notice that student $s01$ is matched with his/her first choice, whereas student $s05$ is matched only with his/her fifth choice. We may inspect in Listing 3.34 below the correlation quality of this fairest *Gale-Shapley* matching with respect to the individual students and internships matching preferences.

Listing 3.34: Correlations with individual students and internships matching preferences

```

1 >>> gsm.showMatchingFairness()
2 Students correlations:
3   's01': +1.000, 's02': +0.778, 's03': +0.333
4   's04': +0.778, 's05': -0.111, 's06': +0.333
5   's07': +0.556, 's08': +0.111, 's09': +0.778
6   's10': +0.556
7 Students average correlation (a) : 0.511
8 Students standard deviation      : 0.344
9 -----
10 Internship correlations:
11   'i01': +1.000, 'i02': +1.000, 'i03': +0.333
12   'i04': +0.778, 'i05': +0.778, 'i06': +0.556
13   'i07': +1.000, 'i08': +1.000, 'i09': +0.556
14   'i10': +0.333
15 Internships average correlation (b) : 0.733
16 Internship standard deviation      : 0.273
17 -----
18 Average correlation      : 0.622
19 Standard Deviation       : 0.323
20 Unfairness |(a) - (b)| : 0.222

```

In Listing 3.34 Line 3 above we see confirmed that student $s01$ gets indeed his/her first choice. Notice also in Line 4 that student $s05$ is the only one who shows a slightly negative correlation (-0.111). On average the students all together obtain a quite high correlation index of +0.511 (see Line 7).

The internships are however better served, as $i01$, $i02$, $i07$ and $i08$ get their first choices and no internship shows a negative correlation with our fairness enhanced matching (see Lines 11-14). The average correlation is hence higher (+0.733 see Line 15). The average correlation index considering all students and internships together is also quite high (+0.622), but the difference between the students and the internships average correlations leads to an unfairness index of $+0.733 - 0.511 = 0.222$. The *Gale-Shapley* pairing solution clearly better serves the internships than the students.

Mind that all *deferred acceptance* algorithms, by returning always the best stable matching for the proposing side and the worst stable matching for the other side, implement indeed essentially unfair intergroup pairing solvers and are hence not recommended for computing **fair** pairing solutions. Yet, finding an optimal fairest pairing solution in our case here would mean to test the fairness of each one of the $10! = 3628800$ potential matching solutions. This brute force approach is not tractable.

Using a fairness enhancing heuristic

It is recommended to use the `pairings.FairnessEnhancedInterGroupMatching` constructor which implements, starting from any initial potential matching, a fairness enhancing heuristic by testing swappings of right hand sides of pairs. If no initial matching is given, the fairness enhancing procedure starts from two initial matchings, a left one that matches sn with in for $n = 1$ to $n = 10$, and a right one matching sn with im where $n = 1$ to $n = 10$ and $m = 11 - n$. The fairest pairing solution will eventually be returned (see tutorial on [computing fair intergroup pairings](#) (page 141)).

Listing 3.35: Fairness enhanced intergroup matching

```
1 >>> from pairings import FairnessEnhancedInterGroupMatching
2 >>> fem = FairnessEnhancedInterGroupMatching(lvpS,lvpI,
3 ...                                         initialMatching=None)
4 >>> fem.matching
5  [['s01', 'i07'], ['s02', 'i09'], ['s03', 'i10'], ['s04', 'i03'], ['s05',
6  ↪ 'i08'],
7  ['s06', 'i01'], ['s07', 'i06'], ['s08', 'i04'], ['s09', 'i02'], ['s10',
8  ↪ 'i05']]
```

In Listing 3.35 Lines 5-6 we notice that we recover unfortunately the same previous unfair *Gale-Shapley* matching.

In order to try to lower the unfairness of the pairing solution, it appears opportune helping the fairness enhancing heuristic by providing as initial matching a best *Copeland* matching. This matching is assembled via a ranked pairs algorithm based on The *Copeland* matching fitness scores from the student as well as the internship perspective already used by the fairness enhancing procedure⁶⁹. The `pairings` module provides therefore the `BestCopelandInterGroupMatching` class which constructs a complete bipartite graph where the characteristic values of the edges represent such matching fitness scores computed for each individual match (in Listing 3.36 see Lines 4-15 below).

Listing 3.36: Best Copeland initial matching

```
1 >>> from pairings import BestCopelandInterGroupMatching
2 >>> bcm = BestCopelandInterGroupMatching(lvpS,lvpI)
3 >>> bcm.showEdgesCharacteristicValues()
4
5      | 'i01' 'i02' 'i03' 'i04' 'i05' 'i06' 'i07' 'i08' 'i09' 'i10'
6  -----| -----
7  's01' | +12    +8    +8    +44   +44   +56   +72   +56   +64   +48
8  's02' | +16    +36   +56   +16   +60   +40   +56   +28   +60   +52
9  's03' | +28    +16   +32   +12   +4    +32   +40   +60   +44   +48
10 's04' | +44    +36   +56   +40   +48   +28   +4    +48   +52   +36
11 's05' | +56    +40   +40   +16   +40   +40   +40   +52   +4    +40
12 's06' | +60    +24   +56   +56   +28   +20   +28   +16   +40   +40
13 's07' | +56    +52   +24   +8    +36   +56   +28   +52   +16   +48
14 's08' | +20    +36   +44   +52   +44   +40   +44   +8    +40   +0
```

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⁶⁹ See [computing fair intergroup pairings](#) (page 141)

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```

14 's09' | +20    +68    +36    +20    +28    +0    +24    +44    +24    +12
15 's10' | +40    +36    +52    +36    +60    +8    +40    +12    +16    +44
16 Valuation domain: [-72;+72]
17 >>> bcm.showMatchingWithFitnessScores()
18 ['s01', 'i07'](72), ['s09', 'i02'](68), ['s02', 'i05'](60),
19 ['s03', 'i08'](60), ['s06', 'i01'](60), ['s04', 'i03'](56),
20 ['s07', 'i06'](56), ['s08', 'i04'](52), ['s10', 'i10'](44),
21 ['s05', 'i09'](4)

```

In Lines 18-21 above we notice that the pair ['s01', 'i07'] shows the highest matching fitness score of 72, followed by the pair ['s09', 'i02'] with a fitness score of +68. Three further pairs show a fitness score of 60, and so on. The last remaining matched pair is ['s05', 'i09'] with a fitness score of only +4.

This *bcm.matching* is submitted as initial matching to our fairness enhancing algorithm (see Listing 3.37 Line 2 below). After four enhancing iterations, the resulting fairest pairing solution is shown in Lines 4-5.

Listing 3.37: Best Copeland initial matching

```

1 >>> fecop = FairnessEnhancedInterGroupMatching(lvpS,lvpI,
2 ...                               initialMatching=bcm.matching)
3 >>> fecop.iterations
4 4
5 >>> fecop.matching
6 [[['s01', 'i07'], ['s02', 'i09'], ['s03', 'i08'], ['s04', 'i03'], ['s05',
7 ↪ 'i10'],
8 ['s06', 'i01'], ['s07', 'i06'], ['s08', 'i04'], ['s09', 'i02'], ['s10',
9 ↪ 'i05']]]
10 >>> fecop.showMatchingFairness()
11 Students correlations:
12 's01': +1.000, 's02': +0.778, 's03': +1.000
13 's04': +0.778, 's05': +0.333, 's06': +0.333
14 's07': +0.556, 's08': +0.111, 's09': +0.778
15 's10': +0.556
16 Students average correlation (a) : 0.622
17 Students standard deviation      : 0.297
18 -----
19 Internship correlations:
20 'i01': +1.000, 'i02': +1.000, 'i03': +0.333
21 'i04': +0.778, 'i05': +0.778, 'i06': +0.556
22 'i07': +1.000, 'i08': +0.333, 'i09': +0.556
23 'i10': -0.111
24 Internships average correlation (b) : 0.622
25 Internships standard deviation     : 0.364
26 -----
27 Average correlation      : 0.622

```

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```
26 Standard Deviation      : 0.323
27 Unfairness |(a) - (b)| : 0.000
```

We get now the same average correlation index of +0.622 for all students and for all internships (see Lines 14 and 24). No unfairness anymore is observed with this pairing solution. Two students get their first choices and three students their second choices. No student gets a negative correlation (see Lines 10-13). Whereas three internships get their first choices and two their second choices. Internship $i10$ gets however now a slightly negative correlation index as student $s05$ is only its 6th choice (see Lines 18-22).

Contrary to *deferred acceptance* algorithms, our fairness enhancing heuristic does not require complete linear voting profiles for computing a fair pairing result. Partial linear voting profiles or bipolar approval-disapproval voting profiles may be taken more realistically into account.

Using bipolar approval-disapproval voting profiles

An interesting experiment consists now in dividing the given complete linear voting profiles *lvpStudents.py* and *lvpInternships.py* into three parts: the three best-ranked options are considered to be approved and the three last-ranked are considered to be disapproved.

The `LinearVotingProfile` class provides a special `save2BipolarApprovalProfile` method for extracting from a given complete linear voting profile a corresponding bipolar approval profile with two parameters for controlling the number of approved as well as the number of disapproved candidates. With the `votingProfiles.BipolarApprovalVotingProfile` class we may reload these stored bipolar approval profiles (see Listing 3.38 Line 2-4).

Listing 3.38: Bipolar approval matching profiles

```
1 >>> lvpS.save2BipolarApprovalProfile(fileName='bapStudents',
2 ...                               approvalIndex=2,disapprovalIndex=7)
3 >>> from votingProfiles import BipolarApprovalVotingProfile
4 >>> bapS = BipolarApprovalVotingProfile('bapStudents')
5 >>> bapS.showBipolarApprovals()
6 Bipolar approval ballots
7 -----
8 's01': Approvals: ['i07','i09','i10'], Disapprovals: ['i05','i02','i03']
9 's02': Approvals: ['i05','i09','i03'], Disapprovals: ['i08','i02','i04']
10 's03': Approvals: ['i08','i09','i07'], Disapprovals: ['i02','i04','i05']
11 's04': Approvals: ['i08','i03','i09'], Disapprovals: ['i10','i04','i07']
12 's05': Approvals: ['i03','i01','i05'], Disapprovals: ['i06','i04','i09']
13 's06': Approvals: ['i04','i10','i05'], Disapprovals: ['i02','i09','i07']
14 's07': Approvals: ['i01','i02','i06'], Disapprovals: ['i04','i07','i09']
15 's08': Approvals: ['i07','i09','i03'], Disapprovals: ['i08','i01','i10']
16 's09': Approvals: ['i03','i02','i08'], Disapprovals: ['i10','i09','i06']
17 's10': Approvals: ['i02','i10','i05'], Disapprovals: ['i01','i08','i06']
18 >>> lvpI.save2BipolarApprovalProfile(fileName='bapInternships',
```

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```

19                                approvalIndex=2,disapprovalIndex=7)
20 >>> bapI = BipolarApprovalVotingProfile('bapInternships')
21 >>> bapI.showBipolarApprovals()
22 Bipolar approval ballots
23 -----
24 'i01': Approvals: ['s06','s10','s04'], Disapprovals: ['s09','s02','s01']
25 'i02': Approvals: ['s09','s02','s05'], Disapprovals: ['s03','s01','s10']
26 'i03': Approvals: ['s06','s10','s02'], Disapprovals: ['s01','s05','s09']
27 'i04': Approvals: ['s04','s08','s01'], Disapprovals: ['s03','s09','s07']
28 'i05': Approvals: ['s01','s10','s04'], Disapprovals: ['s09','s03','s06']
29 'i06': Approvals: ['s01','s05','s07'], Disapprovals: ['s10','s06','s09']
30 'i07': Approvals: ['s01','s02','s06'], Disapprovals: ['s08','s04','s09']
31 'i08': Approvals: ['s05','s01','s07'], Disapprovals: ['s10','s06','s08']
32 'i09': Approvals: ['s06','s01','s02'], Disapprovals: ['s08','s05','s10']
33 'i10': Approvals: ['s02','s07','s04'], Disapprovals: ['s06','s09','s08']

```

In Line 8 above, we may notice for instance that student $s01$ approves the internships $i07$, $i09$ and $i10$ and disapproves internships $i05$, $i02$ and $i03$. Reciprocally, students $s01$, $s02$ and $s06$ are approved by internship $i07$ whereas students $s08$, $s04$ and $s09$ are disapproved (see Line 30).

In Listing 3.39 we can now submit these reciprocal bipolar approval profiles $bapS$ and $bapI$ to our fairness enhancing heuristic and starting as before the fairness enhancing procedure from a best *Copeland* matching.

Listing 3.39: Resolving the intergroup group pairing problem

```

1 >>> bcm = BestCopelandInterGroupMatching(bapS,bapI)
2 >>> fem = FairnessEnhancedInterGroupMatching(bapS,bapI,
3 ...                               initialMatching=bcm.matching)
4 >>> fem.iterations
5 7
6 >>> fem.matching
7 [[['s01','i07'], ['s02','i09'], ['s03','i10'], ['s04','i01'], ['s05','i08'],
8   ['s06','i04'], ['s07','i06'], ['s08','i03'], ['s09','i02'], ['s10','i05']]]
9 >>> fem.showMatchingFairness()
10 -----
11 Students correlations:
12   's01': +1.000, 's02': +1.000, 's03': +0.000, 's04': +0.000,
13   's05': +0.000, 's06': +1.000, 's07': +1.000, 's08': +1.000,
14   's09': +1.000, 's10': +1.000
15 Average correlation (a) : 0.700
16 Standard deviation      : 0.483
17 -----
18 Internships correlations:
19   'i01': +1.000, 'i02': +1.000, 'i03': +0.000, 'i04': +0.000,

```

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```
20 'i05': +1.000, 'i06': +1.000, 'i07': +1.000, 'i08': +1.000,
21 'i09': +1.000, 'i10': +0.000
22 Average correlation (b) : 0.700
23 Standard deviation      : 0.483
24 -----
25 Average overall correlation : 0.700
26 Standard Deviation        : 0.470
27 Unfairness |(a) - (b)|     : 0.000
```

Above we may notice that our fairness enhancing heuristic finds in 7 iterations a very fair pairing solution where both the students and the internships are equally served (see Lines 15, 22 and 27). Seven students and seven internships out of ten get proposed an approved match and no student or internship is proposed a disapproved match.

3.6 Exercises

We propose hereafter some decision problems which may serve as exercises and exam questions in an *Algorithmic Decision Theory* Course. They cover *selection*, *ranking* and *rating* decision problems. The exercises are marked as follows: § (warming up), §§ (home work), §§§ (research work).

- *Who will receive the best student award? (§)* (page 249)
- *How to fairly rank movies (§)* (page 250)
- *What is your best choice recommendation? (§)* (page 251)
- *What is the best public policy? (§§)* (page 253)
- *A fair diploma validation decision (§§§)* (page 253)

Solutions should be supported both by computational Python code using the **Digraph3** programming resources as well as by methodological and algorithmic arguments from the Algorithmic Decision Theory Lectures.

Who will receive the best student award? (§)

Data

Below in Table 3.3 you see the actual grades obtained by four students : *Ariana* (A), *Bruce* (B), *Clare* (C) and *Daniel* (D) in five courses: *C1*, *C2*, *C3*, *C4* and *C5* weighted by their respective ECTS points.

Table 3.3: Grades obtained by the students

Course ECTS	C1	C2	C3	C4	C5
Ariana (A)	11	13	9	15	11
Bruce (B)	12	9	13	10	13
Clare (C)	8	11	14	12	14
Daniel (D)	15	10	12	8	13

The grades shown in Table 3.3 are given on an ordinal performance scale from 0 pts (weakest) to 20 pts (highest). Assume that the grading admits a *preference* threshold of 1 points. No *considerable* performance differences are given. The more ECTS points, the more importance a course takes in the curriculum of the students. An award is to be granted to the *best* amongst these four students.

Questions

1. Edit a *PerformanceTableau* (page 54) instance with the data shown above.
2. Who would you nominate ?
3. Explain and motivate your selection algorithm.
4. Assume that the grading may actually admit an *indifference* threshold of 1 point and a *preference* threshold of 2 points. How stable is your result with respect to the actual preference discrimination power of the grading scale?

How to fairly rank movies (§)

Data

- File `graffiti03.py` contains a performance tableau about the rating of movies to be seen in the city of Luxembourg, February 2003. Its content is shown in Fig. 3.20 below.

```

1 >>> from perfTabs import PerformanceTableau
2 >>> t = PerformanceTableau('graffiti03')
3 >>> t.showHTMLPerformanceHeatmap(WithActionNames=True,
4 ...                               pageTitle='Graffiti Star wars',
5 ...                               rankingRule=None,colorLevels=5,
6 ...                               ndigits=0)

```

Graffiti Star wars

movies (id) \ critics	jh	vt	ap	as	cf	cn	cs	dr	jt	mk	mr	rr	td
weights	+2.00	+2.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00	+1.00
Ah si j'étais riche (ah)	1	NA	NA	NA	NA	-1	1	NA	1	2	NA	1	3
A walk to remember (aw)	NA	NA	-1	NA	1	NA	2	NA	-1	1	NA	1	NA
Bend it like Beckham (bb)	2	1	2	1	2	2	3	2	2	3	2	3	1
Demonlover (dl)	1	-1	-1	-1	-1	NA	-1	1	1	NA	1	1	1
Gangs of New York (gny)	3	3	2	4	2	4	2	3	4	2	4	3	2
Ghost Ship (gs)	NA	NA	1	NA	-1	NA	1	1	1	NA	-1	-1	-1
El Hija de la Novia (hn)	2	1	3	NA	3	2	2	NA	2	3	2	2	NA
Lantana (la)	3	3	3	2	3	3	2	2	3	3	4	3	NA
Lord of the Rings - The Two Towers (lor)	3	2	2	3	3	NA	3	4	4	1	2	2	2
The Magdalene Sisters (ma)	3	3	NA	NA	NA	3	2	3	3	3	2	2	3
Mr. Deeds (md)	NA	NA	1	1	-1	NA	NA	-1	1	-1	NA	-1	1
Mon Idole (mi)	1	1	NA	-1	NA	1	-1	NA	2	NA	NA	-1	2
the Slaton Sea (sa)	2	NA	NA	NA	NA	NA	2	NA	1	3	1	NA	NA
the santa Clause 2 (sc)	NA	NA	1	NA	1	NA	-1	NA	1	1	NA	1	NA
Sweet home Alabama (sha)	-1	NA	2	-1	1	1	2	2	2	1	1	1	NA
Sweet Sixteen (ss)	3	3	3	3	3	4	2	3	3	3	3	1	3
24 heures de la vie d'une femme (vf)	1	NA	NA	NA	NA	1	NA	NA	1	NA	NA	1	1

Color legend:

quantile	20.00%	40.00%	60.00%	80.00%	100.00%
----------	--------	--------	--------	--------	---------

Fig. 3.20: Graffiti magazine's movie ratings from February 2003

The critic's opinions are expressed on a 7-graded scale: -2 (two zeros, *I hate*), -1 (one zero, *I don't like*), 1 (one star, *maybe*), 2 (two stars, *good*), 3 (three stars, *excellent*), 4 (four stars, *not to be missed*), and 5 (five stars, *a master piece*). Notice the many missing data (NA) when a critic had not seen the respective movie. Mind also that the ratings of two movie critics (*jh* and *vt*) are given a higher significance weight.

Questions

1. The Graffiti magazine suggest a best rated movie with the help of an average number of stars, ignoring the missing data and any significance weights of the critics. By taking into account missing data and varying significance weights, how may one find the best rated movie without computing any average rating scores ?
2. How would one rank these movies so as to at best respect the weighted rating opinions of each movie critic ?
3. In what ranking position would appear a movie not seen by any movie critic ? Confirm computationally the answer by adding such a fictive, *not at all evaluated*, movie to the given performance tableau instance.
4. How robust are the preceeding results when the significance weights of the movie critics are considered to be only ordinal grades ?

What is your best choice recommendation? (§)

Data⁴⁶

A person, who wants to by a TV set, retains after a first selection, eight potential TV models. To make up her choice these eight models were evaluated with respect to three

⁴⁶ The data is taken from Ph. Vincke, *Multicriteria Decision-Aid*, John Wiley & Sons Ltd, Chichester UK 1992, p.33-35.

decision objectives of *equal importance*: - **Costs** of the set (to be minimized); - **Picture and Sound** quality of the TV (to be maximized); - **Maintenace contract** quality of the provider (to be maximized).

The **Costs** objective is assessed by the price of the TV set (criterion Pr to be minimized). *Picture* quality (criterion Pq), *Sound* quality (criterion Sq) and *Maintenace contract* quality (criterion Mq) are each assessed on a four-level qualitative performance scale: -1 (*not good*), 0 (*average*), 1 (*good*) and 2 (*very good*).

The actual evaluation data are gathered in Table 3.4 below.

Table 3.4: Performance evaluations of the potential TV sets

Criteria Significance	Pr (€) 2	Pq 1	Sq 1	Mq 2
Model T1	-1300	2	2	0
Model T2	-1200	2	2	1
Model T3	-1150	2	1	1
Model T4	-1000	1	1	-1
Model T5	-950	1	1	0
Model T6	-950	0	1	-1
Model T7	-900	1	0	-1
Model T8	-900	0	0	0

The *Price* criterion Pr supports furthermore an *indifference* threshold of 25.00 € and a *preference* threshold of 75.00 €. No considerable performance differences (*veto thresholds*) are to be considered.

Questions

1. Edit a *PerformanceTableau* (page 54) instance with the data shown above and illustrate its content by best showing *objectives*, *criteria*, *decision alternatives* and *performance table*. If needed, write adequate python code.
2. What is the best TV set to recommend?
3. Illustrate your best choice recommendation with an adequate graphviz drawing.
4. Explain and motivate your selection algorithm.
5. Assume that the qualitative criteria: *Picture* quality (Pq), *Sound* quality (Sq), and *Maintenace contract* quality (Mq), are all three considered to be *equi-significant* and that the significance of the Price criterion (Pr) equals the significance of these three quality criteria taken together. How stable is your best choice recommendation with respect to changing these criteria significance weights?

What is the best public policy? (§§)

Data files

- File `perfTab_1.py` contains a *3 Objectives performance tableau* (page 74) with 100 performance records concerning public policies evaluated with respect to an economic, a societal and an environmental public decision objective.
- File `historicalData_1.py` contains a performance tableau of the same kind with 2000 historical performance records.

Questions

1. Illustrate the content of the given `perfTab_1.py` performance tableau by best showing *objectives, criteria, decision alternatives* and *performance table*. If needed, write adequate python code.
2. Construct the corresponding bipolar-valued outranking digraph. How *confident* and/or *robust* are the apparent outranking situations?
3. What are apparently the 5 best-ranked decision alternatives in your decision problem from the different decision objectives point of views and from a global fair compromise view? Justify your ranking approach from a methodological point of view.
4. How would you rate your 100 public policies into relative deciles classes ?
5. Using the given historical records in `historicalData_1.py`, how would you rate your 100 public policies into absolute deciles classes ? Explain the differencea you may observe between the absolute and the previous relative rating result.
6. Select among your 100 potential policies a shortlist of up to 15 potential first policies, all reaching an absolute performance quantile of at least 66.67%.
7. Based on the previous best policies shortlist (see Question 6), what is your eventual best-choice recommendation? Is it perhaps an unopposed best choice by all three objectives?

A fair diploma validation decision (§§§)

Data

Use the `RandomAcademicPerformanceTableau` constructor from the **Digraph3** Python resources for generating realistic random students performance tableaux concerning a curriculum of nine ECTS weighted Courses. Assume that all the gradings are done on an integer scale from 0 (weakest) to 20 (best). It is known that all grading procedures are inevitably imprecise; therefore we will assume an indifference threshold of 1 point and a preference theshold of 2 points. Thurthermore, a performance difference of more than 12 points is considerable and will trigger an outranking polarisation. To validate eventually their curriculum, the students are required to obtain more or less 10 points in each course.

Questions

1. Design and implement a fair diploma validation decision rule based on the grades obtained in the nine Courses.
2. Run simulation tests with random students performance tableaux for validating your design and implementation.

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4 Working with big outranking digraphs

This part introduces python resources for tackling large and big outranking digraphs. First we introduce a sparse model of large outranking digraphs ($\text{order} < 1000$). In a second section we show how to use multiprocessing resources for working with multiple threads in parallel ($\text{order} < 10000$). Finally, we introduce multiprocessing C-versions of the main Digraph3 modules for working with very big outranking digraphs ($\text{order} > 10000$).

- *Sparse bipolar-valued outranking digraphs* (page 254)
- *Using Digraph3 multiprocessing resources* (page 259)
- *On ranking big outranking digraphs* (page 263)

4.1 Sparse bipolar-valued outranking digraphs

- *The sparse pre-ranked outranking digraph model* (page 254)
- *Ranking pre-ranked sparse outranking digraphs* (page 258)

The `RatInbByRelativeQuantilesDigraph` constructor gives via the rating by relative quantiles a linearly ordered decomposition of the corresponding bipolar-valued outranking digraph (see Listing 2.50). This decomposition leads us to a new **sparse pre-ranked** outranking digraph model.

The sparse pre-ranked outranking digraph model

We may notice that a given outranking digraph -the association of a set of decision alternatives and an outranking relation- is, following the methodological requirements of the outranking approach, necessarily associated with a corresponding performance tableau. And, we may use this underlying performance tableau for linearly decomposing the set of potential decision alternatives into **ordered quantiles equivalence classes** by using the quantiles sorting technique seen in the previous Section.

In the coding example shown in Listing 4.1 below, we generate for instance, first (Lines 2-3), a simple performance tableau of 75 decision alternatives and, secondly (Lines 4),

we construct the corresponding `PreRankedOutrankingDigraph` instance called `prg`. Notice by the way the `BigData` flag (Line 3) used here for generating a parsimoniously commented performance tableau.

Listing 4.1: Computing a *pre-ranked* sparse outranking digraph

```

1  >>> from randomPerfTabs import RandomPerformanceTableau
2  >>> tp = RandomPerformanceTableau(numberOfActions=75,
3  ...                               BigData=True, seed=100)
4  >>> from sparseOutrankingDigraphs import \
5  ...                               PreRankedOutrankingDigraph
6  >>> prg = PreRankedOutrankingDigraph(tp, quantiles=5)
7  >>> prg
8  *----- Object instance description -----*
9  Instance class      : PreRankedOutrankingDigraph
10 Instance name       : randomperftab_pr
11 # Actions           : 75
12 # Criteria          : 7
13 Sorting by         : 5-Tiling
14 Ordering strategy  : average
15 # Components        : 9
16 Minimal order      : 1
17 Maximal order      : 25
18 Average order      : 8.3
19 fill rate          : 20.432%
20 Attributes          : ['actions', 'criteria', 'evaluation', 'NA', 'name',
21   'order', 'runTimes', 'dimension', 'sortingParameters',
22   'valuationdomain', 'profiles', 'categories', 'sorting',
23   'decomposition', 'nbrComponents', 'components',
24   'fillRate', 'minimalComponentSize', 'maximalComponentSize', ... ]

```

The ordering of the 5-tiling result is following the **average** lower and upper quintile limits strategy (see previous section and Listing 4.1 Line 14). We obtain here 9 ordered components of minimal order 1 and maximal order 25. The corresponding **pre-ranked decomposition** may be visualized as follows.

Listing 4.2: The quantiles decomposition of a pre-ranked outranking digraph

```

1  >>> prg.showDecomposition()
2  *--- quantiles decomposition in decreasing order---*
3  c1. ]0.80-1.00] : [5, 42, 43, 47]
4  c2. ]0.60-1.00] : [73]
5  c3. ]0.60-0.80] : [1, 4, 13, 14, 22, 32, 34, 35, 40,
6    41, 45, 61, 62, 65, 68, 70, 75]
7  c4. ]0.40-0.80] : [2, 54]
8  c5. ]0.40-0.60] : [3, 6, 7, 10, 15, 18, 19, 21, 23, 24,

```

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```

9          27, 30, 36, 37, 48, 51, 52, 56, 58,
10         63, 67, 69, 71, 72, 74]
11 c6. ]0.20-0.60] : [8, 11, 25, 28, 64, 66]
12 c7. ]0.20-0.40] : [12, 16, 17, 20, 26, 31, 33, 38, 39,
13             44, 46, 49, 50, 53, 55]
14 c8. ] <-0.40] : [9, 29, 60]
15 c9. ] <-0.20] : [57, 59]
```

The highest quintile class ([80%-100%]) contains decision alternatives 5, 42, 43 and 47. Lowest quintile class ([-20%]) gathers alternatives 57 and 59 (see Listing 4.2 Lines 3 and 15). We may inspect the resulting sparse outranking relation map as follows in a browser view.

```
>>> prg.showHTMLRelationMap()
```

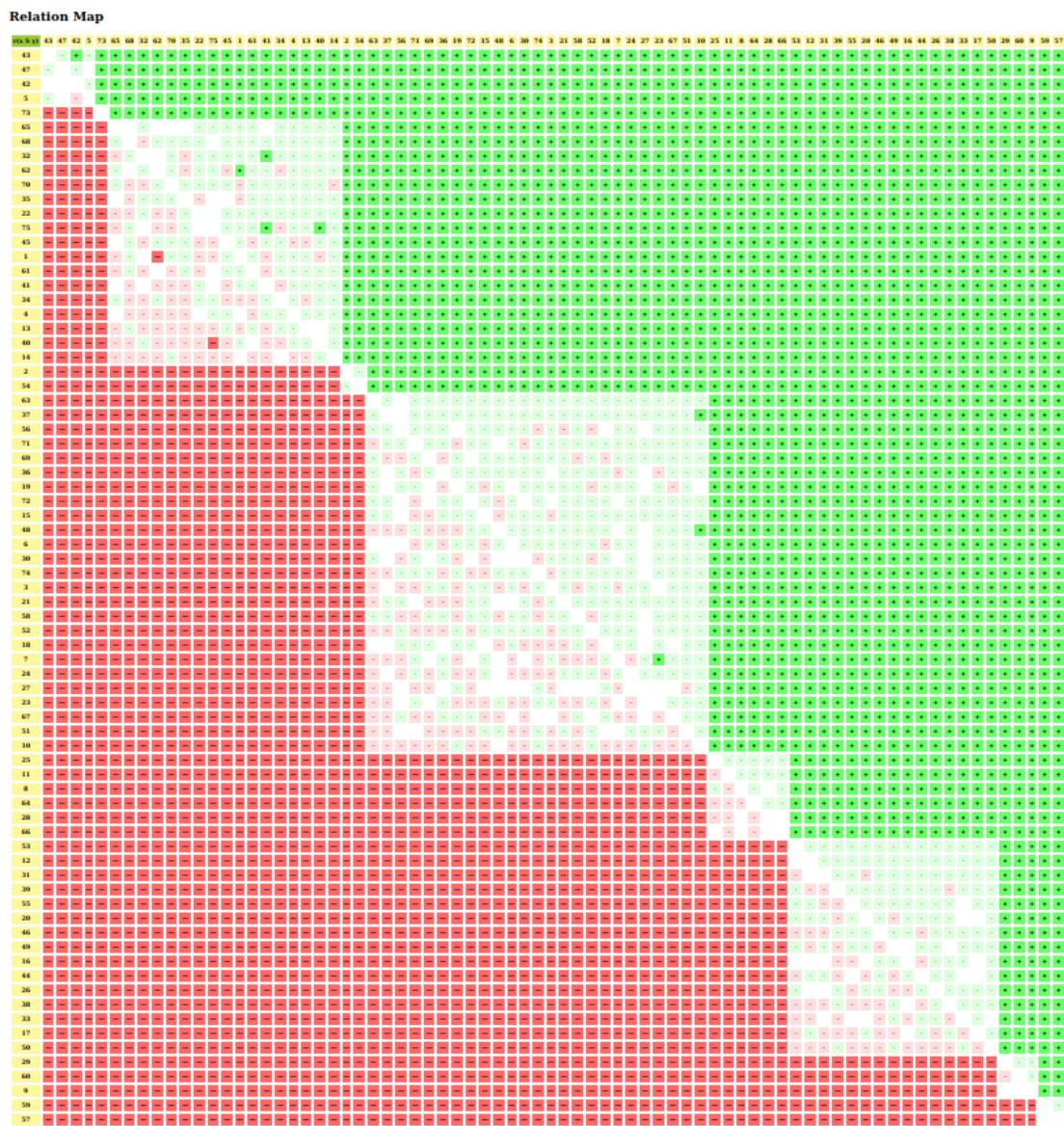


Fig. 4.1: The relation map of a sparse outranking digraph

In Fig. 4.1 we easily recognize the 9 linearly ordered quantile equivalence classes. *Green* and *light-green* show positive **outranking** situations, whereas positive **outranked** situations are shown in **red** and **light-red**. Indeterminate situations appear in white. In each one of the 9 quantile equivalence classes we recover in fact the corresponding bipolar-valued outranking *sub-relation*, which leads to an actual **fill-rate** of 20.4% (see Listing 4.1 Line 20).

We may now check how faithful the sparse model represents the complete outranking relation.

```

1  >>> from outrankingDigraphs import BipolarOutrankingDigraph
2  >>> g = BipolarOutrankingDigraph(tp)
3  >>> corr = prg.computeOrdinalCorrelation(g)
4  >>> g.showCorrelation(corr)
5    Correlation indexes:
6      Crisp ordinal correlation : +0.863
7      Epistemic determination   : 0.315
8      Bipolar-valued equivalence : +0.272

```

The ordinal correlation index between the standard and the sparse outranking relations is quite high (+0.863) and their bipolar-valued equivalence is supported by a mean criteria significance majority of $(1.0+0.272)/2 = 64\%$.

It is worthwhile noticing in Listing 4.1 Line 18 that sparse pre-ranked outranking digraphs do not contain a *relation* attribute. The access to pairwise outranking characteristic values is here provided via a corresponding *relation()* function.

```

1  def relation(self,x,y):
2      """
3          Dynamic construction of the global
4          outranking characteristic function r(x,y).
5      """
6      Min = self.valuationdomain['min']
7      Med = self.valuationdomain['med']
8      Max = self.valuationdomain['max']
9      if x == y:
10         return Med
11      cx = self.actions[x]['component']
12      cy = self.actions[y]['component']
13      if cx == cy:
14          return self.components[cx]['subGraph'].relation[x][y]
15      elif self.components(cx)['rank'] > self.components[cy]['rank']:
16          return Min
17      else:
18          return Max

```

All reflexive situations are set to the *indeterminate* value. When two decision alternatives belong to a same component -quantile equivalence class- we access the *relation* attribute of the corresponding outranking sub-digraph. Otherwise we just check the respective ranks of the components.

Ranking pre-ranked sparse outranking digraphs

Each one of these 9 ordered components may now be locally ranked by using a suitable ranking rule. Best operational results, both in run times and quality, are more or less equally given with the *Copeland* and the *NetFlows* rules. The eventually obtained linear ordering (from the worst to best) is stored in a *prg.boostedOrder* attribute. A reversed linear ranking (from the best to the worst) is stored in a *prg.boostedRanking* attribute.

Listing 4.3: Showing the component wise *Copeland* ranking

```
1 >>> prg.boostedRanking
2 [43, 47, 42, 5, 73, 65, 68, 32, 62, 70, 35, 22, 75, 45, 1,
3 61, 41, 34, 4, 13, 40, 14, 2, 54, 63, 37, 56, 71, 69, 36,
4 19, 72, 15, 48, 6, 30, 74, 3, 21, 58, 52, 18, 7, 24, 27,
5 23, 67, 51, 10, 25, 11, 8, 64, 28, 66, 53, 12, 31, 39, 55,
6 20, 46, 49, 16, 44, 26, 38, 33, 17, 50, 29, 60, 9, 59, 57]
```

Alternative 43 appears *first ranked*, whereas alternative 57 is *last ranked* (see Listing 4.3 Line 2 and 6). The quality of this ranking result may be assessed by computing its ordinal correlation with the standard outranking relation.

```
1 >>> corr = g.computeRankingCorrelation(prg.boostedRanking)
2 >>> g.showCorrelation(corr)
3 Correlation indexes:
4   Crisp ordinal correlation : +0.807
5   Epistemic determination   :  0.315
6   Bipolar-valued equivalence : +0.254
```

We may also verify below that the *Copeland* ranking obtained from the standard outranking digraph is highly correlated (+0.822) with the one obtained from the sparse outranking digraph.

```
1 >>> from linearOrders import CopelandOrder
2 >>> cop = CopelandOrder(g)
3 >>> print(cop.computeRankingCorrelation(prg.boostedRanking))
4 {'correlation': 0.822, 'determination': 1.0}
```

Noticing the computational efficiency of the quantiles sorting construction, coupled with the separability property of the quantile class membership characteristics computation, we will make usage of the *PreRankedOutrankingDigraph* constructor in the *cythonized Digraph3* modules (page 263) for HPC ranking big and even huge performance tableaux.

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4.2 Using Digraph3 multiprocessing resources

- Computing with multiple threads in parallel (page 259)
- Using the *mpOutrankingDigraphs* module (page 260)
- Setting the Threading parameters (page 262)

Computing with multiple threads in parallel

Modern desktop and laptop computers usually provide a multithreaded CPU which allows to run several threads in parallel⁵³. In the Digraph3 resources we offer this usage with a *Threading*, a *nbrCores* or *nbrOfCPUs* and a *startMethod* parameter (see below Lines 5-6)

```
1  >>> from randomPerfTabs import RandomPerformanceTableau
2  >>> t = RandomPerformanceTableau(numberOfActions=500,
3  ...                               numberOfCriteria=13, seed=1)
4  >>> from outrankingDigraphs import BipolarOutrankingDigraph
5  >>> g = BipolarOutrankingDigraph(t, Threading=True,
6  ...                               nbrCores=10, startMethod='spawn')
7  >>> g
8  *----- Object instance description -----*
9  Instance class      : BipolarOutrankingDigraph
10 Instance name       : rel_randomperftab
11 Actions             : 500
12 Criteria            : 13
13 Size                : 142091
14 Determinateness (%) : 62.08
15 Valuation domain    : [-1.00;1.00]
16 Attributes          : ['name', 'actions', 'ndigits', 'valuationdomain',
17                           'criteria', 'methodData', 'evaluation', 'NA',
18                           'order', 'runTimes', 'startMethod', 'nbrThreads',
19                           'relation', 'gamma', 'notGamma']
20 ---- Constructor run times (in sec.) ----
21 Threads             : 10
22 Start method        : spawn
23 Total time          : 3.34283
24 Data input          : 0.00941
25 Compute relation   : 3.20870
26 Gamma sets          : 0.12471
```

⁵³ When tackling matrix computations it may be possible to further accelerate the computations with a potential GPU. The interested reader may find in the *cuda* directory in the Digraph3 resources an experimental *cudaDigraphs.py* module which uses *numpy* and NVIDIA GPU resources for measuring the speeding up of the element wise computation of the dual, converse and codual transforms and the fusion operation for large (*order* ≥ 10000) *cIntegerOutrankingDigraphs.IntegerBipolarOutrankingDigraph* objects.

The same computation without threading takes about four times more total run time (see above Line 25 and below Line 20).

```

1  >>> g = BipolarOutrankingDigraph(t, Threading=False,
2  ...                               nbrCores=10, startMethod='spawn',
3  ...                               WithConcordanceRelation=False,
4  ...                               WithVetoCounts=False)
5  >>> g
6  *----- Object instance description -----*
7  Instance class      : BipolarOutrankingDigraph
8  Instance name       : rel_randomperftab
9  Actions             : 500
10 Criteria            : 13
11 Size                : 142091
12 Determinateness (%) : 62.08
13 Valuation domain    : [-1.00;1.00]
14 Attributes          : ['name', 'actions', 'ndigits', 'valuationdomain
15   ',
16   'criteria', 'methodData', 'evaluation', 'NA',
17   'order', 'runTimes', 'nbrThreads', 'startMethod
18   ',
19   'relation', 'gamma', 'notGamma']
20 ---- Constructor run times (in sec.) ----
21 Start method        : None
22 Total time          : 12.84823
23 Data input          : 0.00941
24 Compute relation   : 12.73070
25 Gamma sets         : 0.10812

```

These run times were obtained on a common desktop computer equipped with an 11th Gen Intel® Core™ i5-11400 × 12 processor and 16.0 BG of CPU memory.

Using the `mpOutrankingDigraphs` module

A refactored and streamlined multiprocessing `mpOutrankingDigraphs` module for even faster computing bipolar outranking digraphs with up to several hundreds or thousands of decision actions has been added to the `Digraph3` resources (see Lines 2-3 below).

```

1  >>> from mpOutrankingDigraphs import MPBipolarOutrankingDigraph
2  >>> mpg = MPBipolarOutrankingDigraph(t, nbrCores=10,
3  ...                               Normalized=False, startMethod='spawn')
4  >>> mpg
5  *----- Object instance description -----*
6  Instance class      : MPBipolarOutrankingDigraph
7  Instance name       : rel_sharedPerfTab
8  Actions             : 500
9  Criteria            : 13
10 Size                : 142091

```

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```

11 Determinateness (%) : 62.08
12 Valuation domain : [-13.00;13.00]
13 Attributes : ['name', 'actions', 'order', 'criteria',
14                 'objectives', 'NA', 'evaluation', 'startMethod',
15                 'nbrThreads', 'relation',
16                 'largePerformanceDifferencesCount',
17                 'valuationdomain', 'gamma', 'notGamma',
18                 'runTimes']
19 ---- Constructor run times (in sec.) ----
20 Threads : 10
21 Start method : 'spawn'
22 Total time : 1.41698
23 Data input : 0.00006
24 Compute relation : 1.27468
25 Gamma sets : 0.14207

```

Notice also in Line 16 above, that this computation provides the *largePerformanceDifferencesCount* attribute containing the results of the considerable performance differences counts. Setting parameter *WithVetoCounts* to *True* for the *"outrankingDigraphs.BipolarOutrankingDigraph* constructor provides the same attribute, but adds about a second to the total run time of 13 seconds.

This attribute allows to print out the relation table with the considerable performance differences counts decoration (see Line 1 below).

```

1 >>> mpg.showRelationTable(hasLPDDenotation=True,toIndex=5)
2 * ---- Relation Table ----
3 r/(lpd)|  'a001'   'a002'   'a003'   'a004'   'a005'
4 -----|-----
5 'a001' |  +13.00    -1.00    +1.00    +3.00    -1.00
6      |  (+0,+0)  (+0,+0)  (+0,+0)  (+0,+0)  (+0,+0)
7 'a002' |  +3.00    +13.00    +2.00    +13.00    +4.00
8      |  (+0,+0)  (+0,+0)  (+0,+0)  (+1,+0)  (+0,+0)
9 'a003' |  +1.00    +3.00    +13.00    -1.00    +4.00
10     |  (+0,+0)  (+0,+0)  (+0,+0)  (+0,+0)  (+0,+0)
11 'a004' |  +2.00    -13.00    +4.00    +13.00    +0.00
12     |  (+0,+0)  (+0,-1)  (+0,+0)  (+0,+0)  (+0,-1)
13 'a005' |  +4.00    +0.00    -3.00    +13.00    +13.00
14     |  (+0,+0)  (+0,+0)  (+0,+0)  (+1,+0)  (+0,+0)
15 Valuation domain: [-13.000; 13.000]

```

In Lines 7-8 above, we may for instance notice a considerably large positive performance difference when comparing alternatives ‘a002’ and ‘a004’ which results in a polarised *for certain valid* outranking situation: $r(a_{002} \succsim a_{004}) = +13.00$. The converse situation is observed in Lines 11-12 where we may notice the corresponding considerably large negative performance difference leading this time to a polarised *for certain invalid* outranking situation: $r(a_{004} \succsim a_{002}) = -13.00$.

Setting the Threading parameters

Without specifying the number of cores (`nbrCores=None`) or the threading start method (`startMethod=None`), the `cpu_count()` method from the `multiprocessing` (<https://docs.python.org/3/library/multiprocessing.html#module-multiprocessing>) module will be used to detect the number of available cores and the threading start method will be set by default to *spawn*.

It is possible to use instead the *forkserver* or the more traditional Posix *fork* start method (default on Linux)⁵². Mind that the latter method, due to the very architecture of the Python interpreter C code, cannot be safe against specific dead locks leading to hanging or freezing applications and zombie processes.⁵¹

As of Python3.14+, it is possible to run multiple isolated python interpreters in parallel. The `MPBipolarOutrankingDigraph` constructor provides the '`MultipleInterpreters = True`' setting for this purpose. The running interpreter minor version may be checked with '`sys.version_info[1] >= 14`'.

When writing multiprocessing Digraph3 Python scripts not using the Posix *fork* start method, it is furthermore essential to protect the main program code with a `--name__ == '__main__'` test against recursive re-execution (see below).

```
1  >>> from mp0utrankingDigraphs import MPBipolarOutrankingDigraph
2  >>> from randomPerfTabs import RandomPerformanceTableau
3  >>> # main program code
4  >>> if __name__ == '__main__':
5  >>>     import sys
6  >>>     t = RandomPerformanceTableau(numberOfActions=1000,
7  ...                     numberOfCriteria=13, seed=1)
8  >>>     if sys.version_info[1] >= 14:
9  >>>         g = MPBipolarOutrankingDigraph(t,
10 ...                         nbrCores=10,
11 ...                         startMethod='spawn',
12 ...                         MultipleInterpreters=True,
13 ...                         Comments=True)
14 >>> else:
15 >>>     g = MPBipolarOutrankingDigraph(t,
16 ...                         nbrCores=10,
17 ...                         startMethod='spawn',
18 ...                         Comments=True)
19 >>> print(g)
```

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⁵² See the documentation of the `multiprocessing` (<https://docs.python.org/3/library/multiprocessing.html#module-multiprocessing>) module

⁵¹ See <https://britishgeologicalsurvey.github.io/science/python-forking-vs-spawn/>

4.3 On ranking big outranking digraphs

- *C-compiled Python modules* (page 263)
- *Big Data performance tableaux* (page 263)
- *C-implemented integer-valued outranking digraphs* (page 265)
- *The sparse outranking digraph implementation* (page 267)
- *Ranking big sets of decision alternatives* (page 271)

C-compiled Python modules

The Digraph3 collection provides cythonized⁶, i.e. C-compiled and optimised versions of the main python modules for tackling multiple criteria decision problems facing very large sets of decision alternatives (> 10000). Such problems appear usually with a combinatorial organisation of the potential decision alternatives, as is frequently the case in bioinformatics for instance. If HPC facilities with nodes supporting numerous cores (> 20) and big RAM ($> 50\text{GB}$) are available, ranking up to several millions of alternatives (see [BIS-2016]) becomes effectively tractable.

Five cythonized Digraph3 modules, prefixed with the letter *c* and taking a *.pyx* extension, are provided with their corresponding setup tools in the *Digraph3/cython* directory, namely

- *cRandPerfTabs.pyx*
- *cIntegerOutrankingDigraphs.pyx*
- *cIntegerSortingDigraphs.pyx*
- *cSparseIntegerOutrankingDigraphs.pyx*
- *cQuantilesRankingDigraphs.pyx*

Their automatic compilation and installation ($\dots \text{Digraph3\$ make installPip}$), alongside the standard Digraph3 python3 modules, requires the *cython* compiler⁶ ($\dots \$ \text{python3 m pip install cython wheel}$) and a C compiler ($\dots \$ \text{sudo apt install gcc}$). Local *inplace* compilation and installation ($\dots \text{/Digraph3/cython\$ make}$) is provided with a corresponding *makefile* in the *Digraph3/cython* directory.

Big Data performance tableaux

In order to efficiently type the C variables, the *cRandPerfTabs* module provides the usual random performance tableau models, but, with **integer** action keys, **float** performance evaluations, **integer** criteria weights and **float** discrimination thresholds. And, to limit as much as possible memory occupation of class instances, all the usual verbose comments are dropped from the description of the *actions* and *criteria* dictionaries.

⁶ See <https://cython.org/>

```

1  >>> from cRandPerfTabs import cRandomPerformanceTableau
2  >>> t = cRandomPerformanceTableau(numberOfActions=4,numberOfCriteria=2)
3  >>> t
4      ----- PerformanceTableau instance description -----
5  Instance class      : cRandomPerformanceTableau
6  Seed                : None
7  Instance name       : cRandomperftab
8  # Actions           : 4
9  # Criteria          : 2
10 Attributes          : ['randomSeed', 'name', 'actions', 'criteria',
11                           'evaluation', 'weightPreorder']
12 >>> t.actions
13 OrderedDict([(1, {'name': '#1'}), (2, {'name': '#2'}),
14               (3, {'name': '#3'}), (4, {'name': '#4'})])
15 >>> t.criteria
16 OrderedDict([
17     ('g1', {'name': 'RandomPerformanceTableau() instance',
18              'comment': 'Arguments: ; weightDistribution=equisignificant',
19              'weightScale=(1, 1); commonMode=None',
20              'thresholds': {'ind': (10.0, 0.0),
21                             'pref': (20.0, 0.0),
22                             'veto': (80.0, 0.0)},
23              'scale': (0.0, 100.0),
24              'weight': 1,
25              'preferenceDirection': 'max'}),
26     ('g2', {'name': 'RandomPerformanceTableau() instance',
27              'comment': 'Arguments: ; weightDistribution=equisignificant',
28              'weightScale=(1, 1); commonMode=None',
29              'thresholds': {'ind': (10.0, 0.0),
30                             'pref': (20.0, 0.0),
31                             'veto': (80.0, 0.0)},
32              'scale': (0.0, 100.0),
33              'weight': 1,
34              'preferenceDirection': 'max'}))
35 >>> t.evaluation
36     {'g1': {1: 35.17, 2: 56.4, 3: 1.94, 4: 5.51},
37      'g2': {1: 95.12, 2: 90.54, 3: 51.84, 4: 15.42}}
38 >>> t.showPerformanceTableau()
39   Criteria | 'g1'    'g2'
40   Actions  |    1      1
41   -----|-----
42   '#1'    |  91.18   90.42
43   '#2'    |  66.82   41.31
44   '#3'    |  35.76   28.86
45   '#4'    |   7.78   37.64

```

Conversions from the Big Data model to the standard model and vice versa are provided.

```

1 >>> t1 = t.convert2Standard()
2 >>> t1.convertWeight2Decimal()
3 >>> t1.convertEvaluation2Decimal()
4 >>> t1
5     ----- PerformanceTableau instance description -----
6 Instance class      : PerformanceTableau
7 Seed                 : None
8 Instance name       : std_cRandomperftab
9 # Actions            : 4
10 # Criteria           : 2
11 Attributes          : ['name', 'actions', 'criteria', 'weightPreorder',
12                           'evaluation', 'randomSeed']

```

C-implemented integer-valued outranking digraphs

The C compiled version of the bipolar-valued digraph models takes integer relation characteristic values.

```

1 >>> from cRandPerfTabs import cRandomPerformanceTableau
2 >>> t = cRandomPerformanceTableau(numberOfActions=1000,
3                                     ↪numberOfCriteria=2)
4 >>> from cIntegerOutrankingDigraphs import ↪
5             IntegerBipolarOutrankingDigraph
6 >>> g = IntegerBipolarOutrankingDigraph(t, Threading=True, nbrCores=4)
7 >>> g
8     ----- Object instance description -----
9 Instance class      : IntegerBipolarOutrankingDigraph
10 Instance name       : rel_cRandomperftab
11 Actions             : 1000
12 Criteria            : 2
13 Size                : 465024
14 Determinateness     : 56.877
15 Valuation domain   : {'min': -2, 'med': 0, 'max': 2,
16                           'hasIntegerValuation': True}
17 Attributes          : ['name', 'actions', 'criteria', 'totalWeight',
18                           'valuationdomain', 'methodData', 'evaluation',
19                           'order', 'runTimes', 'startMethod',
20                           'nbrThreads', 'relation',
21                           'gamma', 'notGamma']
22 ---- Constructor run times (in sec.) ----
23 Threads             : 4
24 Start method        : spawn
25 Total time          : 1.19811
26 Data input          : 0.00183
27 Compute relation   : 0.91961
28 Gamma sets          : 0.27664

```

On a classic intel-i5-11400x12 equipped PC, the `IntegerBipolarOutrankingDigraph`

constructor takes with four multiprocessing threads about one second for computing a **million** pairwise outranking characteristic values. In a similar multiprocessing setting, the standard `BipolarOutrankingDigraph` class constructor operates about four times slower.

```

1 >>> from outrankingDigraphs import BipolarOutrankingDigraph
2 >>> t1 = t.convert2Standard()
3 >>> g1 = BipolarOutrankingDigraph(t1, Threading=True, nbrCores=4)
4 >>> g1
5     *----- Object instance description -----*
6     Instance class      : BipolarOutrankingDigraph
7     Instance name       : rel_std_cRandomperftab
8     Actions             : 1000
9     Criteria            : 2
10    Size                : 465024
11    Determinateness     : 56.817
12    Valuation domain   : {'min': Decimal('-1.0'),
13                            'med': Decimal('0.0'),
14                            'max': Decimal('1.0'),
15                            'precision': Decimal('0')}
16    ---- Constructor run times (in sec.) ----
17    Threads             : 4
18    Start method        : spawn
19    Total time          : 3.81307
20    Data input          : 0.00305
21    Compute relation    : 3.41648
22    Gamma sets          : 0.39353

```

By far, most of the run time is in each case needed for computing the individual pairwise outranking characteristic values. Notice also below the memory occupations of both outranking digraph instances.

```

1 >>> from digraphsTools import total_size
2 >>> total_size(g)
3 108662777
4 >>> total_size(g1)
5 113564067
6 >>> total_size(g.relation)/total_size(g)
7 0.34
8 >>> total_size(g.gamma)/total_size(g)
9 0.45

```

About 109MB for g and 114MB for $g1$. The standard `Decimal` valued `BipolarOutrankingDigraph` instance $g1$ thus adds nearly 10% to the memory occupation of the corresponding `IntegerBipolarOutrankingDigraph` g instance (see Line 3 and 5 above). 3/4 of this memory occupation is due to the $g.relation$ (34%) and the $g.gamma$ (45%) dictionaries. And these ratios quadratically grow with the digraph order. To limit the object sizes for really big outranking digraphs, we need to abandon the complete implementation of adjacency tables and gamma functions.

The sparse outranking digraph implementation

The idea is to first decompose the complete outranking relation into an ordered collection of equivalent quantile performance classes. Let us consider for this illustration a random performance tableau with 100 decision alternatives evaluated on 7 criteria.

```
1 >>> from cRandPerfTabs import cRandomPerformanceTableau
2 >>> t = cRandomPerformanceTableau(numberOfActions=100,
3 ...                                     numberOfCriteria=7, seed=100)
```

We sort the 100 decision alternatives into overlapping quartile classes and rank with respect to the average quantile limits.

```
1 >>> from cSparseIntegerOutrankingDigraphs import \
2 ...     SparseIntegerOutrankingDigraph
3 >>> sg = SparseIntegerOutrankingDigraph(t, quantiles=4,
4 ...                                         OptimalQuantileOrdering=False,
5 ...                                         Threading=False)
6 >>> sg
7 *----- Object instance description -----
8 Instance class      : SparseIntegerOutrankingDigraph
9 Instance name        : cRandomperftab_mp
10 # Actions           : 100
11 # Criteria          : 7
12 Sorting by          : 4-Tiling
13 Ordering strategy   : average
14 Ranking rule         : Copeland
15 # Components         : 6
16 Minimal order       : 1
17 Maximal order       : 35
18 Average order       : 16.7
19 fill rate           : 24.970%
20 Attributes          : ['runTimes', 'name', 'actions', 'criteria',
21 ...                      'evaluation', 'order', 'dimension',
22 ...                      'sortingParameters', 'nbrOfCPUs',
23 ...                      'valuationdomain', 'profiles', 'categories',
24 ...                      'sorting', 'minimalComponentSize',
25 ...                      'decomposition', 'nbrComponents', 'nd',
26 ...                      'components', 'fillRate',
27 ...                      'maximalComponentSize', 'componentRankingRule',
28 ...                      'boostedRanking']
29 *----- Constructor run times (in sec.) -----
30 Total time           : 0.02336
31 QuantilesSorting    : 0.01150
32 Preordering          : 0.00047
33 Decomposing          : 0.01135
34 Ordering             : 0.00001
```

We obtain in this example here a decomposition into 6 linearly ordered components with

a maximal component size of 35 for component $c3$.

```
1 >>> sg.showDecomposition()
2     *--- quantiles decomposition in decreasing order---*
3 c1. ]0.75-1.00] : [3, 22, 24, 34, 41, 44, 50, 53, 56, 62, 93]
4 c2. ]0.50-1.00] : [7, 29, 43, 58, 63, 81, 96]
5 c3. ]0.50-0.75] : [1, 2, 5, 8, 10, 11, 20, 21, 25, 28, 30, 33,
6                 35, 36, 45, 48, 57, 59, 61, 65, 66, 68, 70,
7                 71, 73, 76, 82, 85, 89, 90, 91, 92, 94, 95, 97]
8 c4. ]0.25-0.75] : [17, 19, 26, 27, 40, 46, 55, 64, 69, 87, 98, 100]
9 c5. ]0.25-0.50] : [4, 6, 9, 12, 13, 14, 15, 16, 18, 23, 31, 32,
10                37, 38, 39, 42, 47, 49, 51, 52, 54, 60, 67, 72,
11                74, 75, 77, 78, 80, 86, 88, 99]
12 c6. ]<-0.25] : [79, 83, 84]
```

A restricted outranking relation is stored for each component with more than one alternative. The resulting global relation map of the first ranked 75 alternatives looks as follows.

```
>>> sg.showRelationMap(toIndex=75)
```

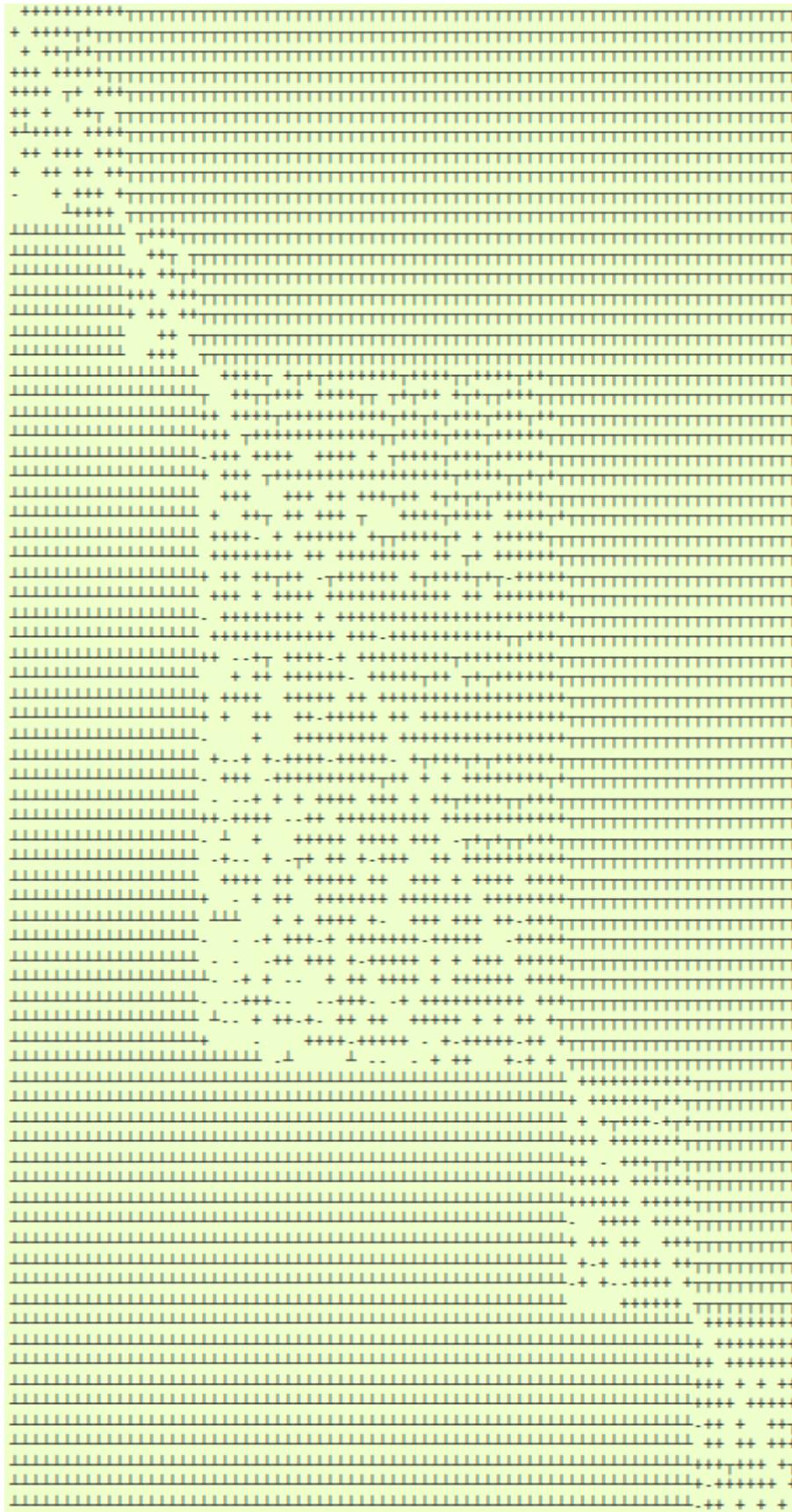


Fig. 4.2: Sparse quartiles-sorting decomposed outranking relation (extract). **Legend:** *outranking* for certain (\top); *outranked* for certain (\perp); more or less *outranking* (+); more or less *outranked* (-); *indeterminate* ().

With a fill rate of 25%, the memory occupation of this sparse outranking digraph *sg* instance takes now only 769kB, compared to the 1.7MB required by a corresponding standard IntegerBipolarOutrankingDigraph instance.

```
>>> print('%.0f kB' % (total_size(sg)/1024) )
769kB
```

For sparse outranking digraphs, the adjacency table is implemented as a dynamic **relation()** function instead of a double dictionary.

```

1 def relation(self, int x, int y):
2     """
3         *Parameters*:
4             * x (int action key),
5             * y (int action key).
6     Dynamic construction of the global outranking
7     characteristic function *r(x S y)*.
8     """
9     cdef int Min, Med, Max, rx, ry
10    Min = self.valuationdomain['min']
11    Med = self.valuationdomain['med']
12    Max = self.valuationdomain['max']
13    if x == y:
14        return Med
15    else:
16        cx = self.actions[x]['component']
17        cy = self.actions[y]['component']
18        rx = self.components[cx]['rank']
19        ry = self.components[cy]['rank']
20        if rx == ry:
21            try:
22                rxiy = self.components[cx]['subGraph'].relation
23                return rxiy[x][y]
24            except AttributeError:
25                componentRanking = self.components[cx]['componentRanking']
26                if componentRanking.index(x) < componentRanking.index(y):
27                    return Max
28                else:
29                    return Min
30            elif rx > ry:
31                return Min
32            else:
33                return Max
```

Ranking big sets of decision alternatives

We may now rank the complete set of 100 decision alternatives by locally ranking with the *Copeland* or the *NetFlows* rule, for instance, all these individual components.

```
1 >>> sg.boostedRanking
2 [22, 53, 3, 34, 56, 62, 24, 44, 50, 93, 41, 63, 29, 58,
3 96, 7, 43, 81, 91, 35, 25, 76, 66, 65, 8, 10, 1, 11, 61,
4 30, 48, 45, 68, 5, 89, 57, 59, 85, 82, 73, 33, 94, 70,
5 97, 20, 92, 71, 90, 95, 21, 28, 2, 36, 87, 40, 98, 46, 55,
6 100, 64, 17, 26, 27, 19, 69, 6, 38, 4, 37, 60, 31, 77, 78,
7 47, 99, 18, 12, 80, 54, 88, 39, 9, 72, 86, 42, 13, 23, 67,
8 52, 15, 32, 49, 51, 74, 16, 14, 75, 79, 83, 84]
```

When actually computing linear rankings of a set of alternatives, the local outranking relations are of no practical usage, and we may furthermore reduce the memory occupation of the resulting digraph by

1. refining the ordering of the quantile classes by taking into account how well an alternative is outranking the lower limit of its quantile class, respectively the upper limit of its quantile class is *not* outranking the alternative;
2. dropping the local outranking digraphs and keeping for each quantile class only a locally ranked list of alternatives.

We provide therefore the `cQuantilesRankingDigraph` class.

```
1 >>> from cSparseIntegerOutrankingDigraphs import \
2 ...     cQuantilesRankingDigraph
3 >>> qr = cQuantilesRankingDigraph(t,4)
4 >>> qr
5 ----- Object instance description -----
6 Instance class      : cQuantilesRankingDigraph
7 Instance name       : cRandomperftab_mp
8 # Actions           : 100
9 # Criteria          : 7
10 Sorting by         : 4-Tiling
11 Ordering strategy  : optimal
12 Ranking rule        : Copeland
13 # Components        : 47
14 Minimal order      : 1
15 Maximal order      : 10
16 Average order      : 2.1
17 fill rate          : 2.566%
18 ----- Constructor run times (in sec.) -----
19 Nbr of threads      : 1
20 Total time          : 0.03702
21 QuantilesSorting   : 0.01785
22 Preordering         : 0.00022
23 Decomposing         : 0.01892
```

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```

24 Ordering : 0.00000
25 Attributes : ['runTimes', 'name', 'actions', 'order',
26 'dimension', 'sortingParameters', 'nbrOfCPUs',
27 'valuationdomain', 'profiles', 'categories',
28 'sorting', 'minimalComponentSize',
29 'decomposition', 'nbrComponents', 'nd',
30 'components', 'fillRate', 'maximalComponentSize',
31 'componentRankingRule', 'boostedRanking']

```

With this *optimised* quantile ordering strategy, we obtain now 47 performance equivalence classes.

```

1 >>> qr.components
2 OrderedDict([
3     ('c01', {'rank': 1,
4         'lowQtileLimit': ']0.75',
5         'highQtileLimit': '1.00'],
6         'componentRanking': [53]}),
7     ('c02', {'rank': 2,
8         'lowQtileLimit': ']0.75',
9         'highQtileLimit': '1.00'],
10        'componentRanking': [3, 23, 63, 50]}),
11    ('c03', {'rank': 3,
12        'lowQtileLimit': ']0.75',
13        'highQtileLimit': '1.00'],
14        'componentRanking': [34, 44, 56, 24, 93, 41]}),
15    ...
16    ...
17    ...
18    ('c45', {'rank': 45,
19        'lowQtileLimit': ']0.25',
20        'highQtileLimit': '0.50'],
21        'componentRanking': [49]}),
22    ('c46', {'rank': 46,
23        'lowQtileLimit': ']0.25',
24        'highQtileLimit': '0.50'],
25        'componentRanking': [52, 16, 86]}),
26    ('c47', {'rank': 47,
27        'lowQtileLimit': ']<',
28        'highQtileLimit': '0.25'],
29        'componentRanking': [79, 83, 84]}])
30 >>> print('%.0f kB' % (total_size(qr)/1024) )
31 208kB

```

We observe an even more considerably less voluminous memory occupation: 208kB compared to the 769kB of the SparseIntegerOutrankingDigraph instance. It is opportune, however, to measure the loss of quality of the resulting *Copeland* ranking when working

with sparse outranking digraphs.

```
1  >>> from cIntegerOutrankingDigraphs import \
2      ...     IntegerBipolarOutrankingDigraph
3  >>> ig = IntegerBipolarOutrankingDigraph(t)
4  >>> print('Complete outranking : %+.4f' \
5      ...     % (ig.computeOrderCorrelation(ig.computeCopelandOrder())\
6      ...         ['correlation']))
7
8  Complete outranking : +0.7474
9  >>> print('Sparse 4-tiling : %+.4f' \
10     ...     % (ig.computeOrderCorrelation(\
11     ...         list(reversed(sg.boostedRanking)))['correlation']))
12
13 Sparse 4-tiling          : +0.7172
14 >>> print('Optimized sparse 4-tiling: %+.4f' \
15     ...     % (ig.computeOrderCorrelation(\
16     ...         list(reversed(qr.boostedRanking)))['correlation']))
17
18 Optimized sparse 4-tiling: +0.7051
```

The best ranking correlation with the pairwise outranking situations (+0.75) is naturally given when we apply the *Copeland* rule to the complete outranking digraph. When we apply the same rule to the sparse 4-tiled outranking digraph, we get a correlation of +0.72, and when applying the *Copeland* rule to the optimised 4-tiled digraph, we still obtain a correlation of +0.71. These results actually depend on the number of quantiles we use as well as on the given model of random performance tableau. In case of Random3ObjectivesPerformanceTableau instances, for instance, we would get in a similar setting a complete outranking correlation of +0.86, a sparse 4-tiling correlation of +0.82, and an optimized sparse 4-tiling correlation of +0.81.

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5 HPC-Ranking of Big Sparse Outranking Digraphs

Following from the separability property of the q -tiles sorting of each action into each q -tiles class, the q -sorting algorithm may be safely split into as much threads as are multiple processing cores available in parallel. Furthermore, the ranking procedure being local to each diagonal component, these procedures may as well be safely processed in parallel threads on each component restricted outranking digraph. Below some examples on different types of computers.

- *On a common 2023 desktop computer* (page 274)
- *On the HPC platform of the University of Luxembourg (Spring 2018)* (page 275)

- On the MeluXina EuroHPC supercomputer (Summer 2024) (page 281)

5.1 On a common 2023 desktop computer

On a common 2023 Terra desktop computer⁵⁶, equipped with a 11th Gen Intel® Core™ i5-11400 × 12 processor, 64.0 GiB of CPU memory and 762.2 GiB storage space, working under Ubuntu 23.10 we may rank a `cRandom3ObjectivesPerformanceTableau` instance of **five hundred thousand** multicriteria performance records in about 104 seconds with about 48 seconds for the quantiles sorting step and 55 seconds for the local components ranking step (see below Lines 42-).

```
1 ./Digraph3/cython$ python3.12
2 Python 3.12.0 (main, Oct  4 2023, 06:27:34) [GCC 13.2.0] on linux
3 >>>
```

```
1 >>> from cRandPerfTabs import \
2 ...     cRandom3ObjectivesPerformanceTableau as cR3ObjPT
3 >>> pt = cR3ObjPT(numberOfActions=500000,
4 ...                 numberOfCriteria=21,
5 ...                 weightDistribution='equiobjectives',
6 ...                 commonScale = (0.0,1000.0),
7 ...                 commonThresholds = [(1.5,0.0),(2.0,0.0),(75.0,0.0)],
8 ...                 commonMode = ['beta','variable',None],
9 ...                 missingDataProbability=0.05,
10 ...                 seed=16)
11 >>> import cSparseIntegerOutrankingDigraphs as iBg
12 >>> qr = iBg.cQuantilesRankingDigraph(pt,quantiles=7,
13 ...                                         quantilesOrderingStrategy='optimal',
14 ...                                         minimalComponentSize=1,
15 ...                                         componentRankingRule='Copeland',
16 ...                                         LowerClosed=False,
17 ...                                         Threading=True,
18 ...                                         tempDir='/tmp',
19 ...                                         nbrOfCPUs=12)
20 >>> qr
21 *----- Object instance description -----*
22 Instance class      : cQuantilesRankingDigraph
23 Instance name       : random3ObjectivesPerfTab_mp
24 Actions             : 500000
25 Criteria            : 21
26 Sorting by          : 7-Tiling
27 Ordering strategy   : optimal
28 Ranking rule         : Copeland
29 Components          : 146579
```

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⁵⁶ <https://www.wortmann.de/>

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```
30 Minimal order      : 1
31 Maximal order     : 115
32 Average order    : 3.4
33 fill rate         : 0.002%
34 Attributes        : ['runTimes', 'name', 'actions', 'order',
35                         'dimension', 'sortingParameters',
36                         'nbrThreads', 'startMethod', 'valuationdomain',
37                         'profiles', 'categories', 'sorting',
38                         'minimalComponentSize', 'decomposition',
39                         'nbrComponents', 'nd', 'components',
40                         'fillRate', 'maximalComponentSize',
41                         'componentRankingRule', 'boostedRanking']
42 ---- Constructor run times (in sec.) ----
43 Threads           : 12
44 StartMethod       : spawn
45 Total time        : 104.48654
46 QuantilesSorting  : 48.09243
47 Preordering       : 1.26480
48 Decomposing      : 55.12919
```

When ordering the 146579 components resulting from a 7-tiling sorting with the *optimal* quantiles ordering strategy, the order of a local component is limited to a maximal size of 115 actions which results in a total pairwise adjacency table fill rate of 0.002% (see Lines 29-33).

5.2 On the HPC platform of the University of Luxembourg (Spring 2018)

Bigger performance tableaux may definitely be ranked with a larger *cpu_count()*. We were using therefore in 2018 the HPC Platform of the University of Luxembourg (<https://hpc.uni.lu/>). The following run times for very big quantiles ranking problems of several millions of multicriteria performance records could be achieved both:

- on Iris -skylake nodes with 28 cores⁷, and
- on the 3TB -bigmem Gaia-183 node with 64 cores⁸,

by running the cythonized python modules in an Intel compiled virtual Python 3.6.5 environment [GCC Intel(R) 17.0.1 –enable-optimizations c++ gcc 6.3 mode] on *Debian 8 Linux*.

⁷ See <https://hpc.uni.lu/systems/iris/>

⁸ See <https://hpc.uni.lu/systems/gaia/>

\gtrless^q outranking relation order	size	q	fill rate	nbr. cores	run time
5 000	25×10^6	4	0.005%	28	0.5"
10 000	1×10^8	4	0.001%	28	1"
100 000	1×10^{10}	5	0.002%	28	10"
1 000 000	1×10^{12}	6	0.001%	64	2'
3 000 000	9×10^{12}	15	0.004%	64	13'
6 000 000	36×10^{12}	15	0.002%	64	41'

Fig. 5.1: HPC-UL Ranking Performance Records (Spring 2018)

Example python session on the HPC-UL Iris-126 -skylake node^{Page 275, 7}

```

1 (myPy365ICC) [rbisdorff@iris-126 Test]$ python
2 Python 3.6.5 (default, May 9 2018, 09:54:28)
3 [GCC Intel(R) C++ gcc 6.3 mode] on linux
4 Type "help", "copyright", "credits" or "license" for more information.
5 >>>

```

```

1 >>> from cRandPerfTabs import \
2 ...     cRandom3ObjectivesPerformanceTableau as cR3ObjPT
3
4 >>> pt = cR3ObjPT(numberOfActions=1000000,
5 ...                 numberOfCriteria=21,
6 ...                 weightDistribution='equiobjectives',
7 ...                 commonScale = (0.0,1000.0),
8 ...                 commonThresholds = [(2.5,0.0),(5.0,0.0),(75.0,0.0)],
9 ...                 commonMode = ['beta','variable',None],
10 ...                 missingDataProbability=0.05,
11 ...                 seed=16)
12
13 >>> import cSparseIntegerOutrankingDigraphs as iBg
14 >>> qr = iBg.cQuantilesRankingDigraph(pt,quantiles=10,
15 ...                                         quantilesOrderingStrategy='optimal',
16 ...                                         minimalComponentSize=1,
17 ...                                         componentRankingRule='NetFlows',
18 ...                                         LowerClosed=False,
19 ...                                         Threading=True,
20 ...                                         tempDir='/tmp',
21 ...                                         nbrOfCPUs=28)
22
23 >>> qr
24 *----- Object instance description -----*
25 Instance class      : cQuantilesRankingDigraph
26 Instance name       : random3ObjectivesPerfTab_mp
27 # Actions           : 1000000

```

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```

28 # Criteria      : 21
29 Sorting by     : 10-Tiling
30 Ordering strategy : optimal
31 Ranking rule    : NetFlows
32 # Components   : 233645
33 Minimal order  : 1
34 Maximal order  : 153
35 Average order  : 4.3
36 fill rate      : 0.001%
37 *---- Constructor run times (in sec.) ----*
38 Nbr of threads  : 28
39 Start method    : fork
40 Total time      : 177.02770
41 QuantilesSorting : 99.55377
42 Preordering      : 5.17954
43 Decomposing     : 72.29356

```

On this 2x14c Intel Xeon Gold 6132 @ 2.6 GHz equipped HPC node with 132GB RAM^{Page 275, 7}, deciles sorting and locally ranking a **million** decision alternatives evaluated on 21 incommensurable criteria, by balancing an economic, an environmental and a societal decision objective, takes us about **3 minutes** (see Lines 37-42 above); with about 1.5 minutes for the deciles sorting and, a bit more than one minute, for the local ranking of the local components.

The optimised deciles sorting leads to 233645 components (see Lines 32-36 above) with a maximal order of 153. The fill rate of the adjacency table is reduced to 0.001%. Of the potential trillion (10^{12}) pairwise outrankings, we effectively keep only 10 millions (10^7). This high number of components results from the high number of involved performance criteria (21), leading in fact to a very refined epistemic discrimination of majority outranking margins.

A non-optimised deciles sorting would instead give at most 110 components with inevitably very big intractable local digraph orders. Proceeding with a more detailed quantiles sorting, for reducing the induced decomposing run times, leads however quickly to intractable quantiles sorting times. A good compromise is given when the quantiles sorting and decomposing steps show somehow equivalent run times; as is the case in our two example sessions: 15 versus 14 seconds and 99.6 versus 77.3 seconds (see Listing before and Lines 41 and 43 above).

Let us inspect the 21 marginal performances of the five best-ranked alternatives listed below.

```

1 >>> pt.showPerformanceTableau(
2 ...                  actionsSubset=qr.boostedRanking[:5],
3 ...                  Transposed=True)
4
5 *---- performance tableau ----*
6 criteria | weights | #773909 #668947 #567308 #578560 #426464

```

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7							
8	'Ec01'	42	969.81	844.71	917.00	NA	808.35
9	'So02'	48	NA	891.52	836.43	NA	899.22
10	'En03'	56	687.10	NA	503.38	873.90	NA
11	'So04'	48	455.05	845.29	866.16	800.39	956.14
12	'En05'	56	809.60	846.87	939.46	851.83	950.51
13	'Ec06'	42	919.62	802.45	717.39	832.44	974.63
14	'Ec07'	42	889.01	722.09	606.11	902.28	574.08
15	'So08'	48	862.19	699.38	907.34	571.18	943.34
16	'En09'	56	857.34	817.44	819.92	674.60	376.70
17	'Ec10'	42	NA	874.86	NA	847.75	739.94
18	'En11'	56	NA	824.24	855.76	NA	953.77
19	'Ec12'	42	802.18	871.06	488.76	841.41	599.17
20	'En13'	56	827.73	839.70	864.48	720.31	877.23
21	'So14'	48	943.31	580.69	827.45	815.18	461.04
22	'En15'	56	794.57	801.44	924.29	938.70	863.72
23	'Ec16'	42	581.15	599.87	949.84	367.34	859.70
24	'So17'	48	881.55	856.05	NA	796.10	655.37
25	'Ec18'	42	863.44	520.24	919.75	865.14	914.32
26	'So19'	48	NA	NA	NA	790.43	842.85
27	'Ec20'	42	582.52	831.93	820.92	881.68	864.81
28	'So21'	48	880.87	NA	628.96	746.67	863.82

The given ranking problem involves 8 criteria assessing the economic performances, 7 criteria assessing the societal performances and 6 criteria assessing the environmental performances of the decision alternatives. The sum of criteria significance weights (336) is the same for all three decision objectives. The five best-ranked alternatives are, in decreasing order: #773909, #668947, #567308, #578560 and #426464.

Their random performance evaluations were obviously drawn on all criteria with a *good* (+) performance profile, i.e. a Beta($\alpha = 5.8661$, $\beta = 2.62203$) law (see the tutorial *generating random performance tableaux* (page 66)).

```

1 >>> for x in qr.boostedRanking[:5]:
2 ...     print(pt.actions[x]['name'],
3 ...           pt.actions[x]['profile'])
4
5 #773909 {'Eco': '+', 'Soc': '+', 'Env': '+'}
6 #668947 {'Eco': '+', 'Soc': '+', 'Env': '+'}
7 #567308 {'Eco': '+', 'Soc': '+', 'Env': '+'}
8 #578560 {'Eco': '+', 'Soc': '+', 'Env': '+'}
9 #426464 {'Eco': '+', 'Soc': '+', 'Env': '+'}
```

We consider now a partial performance tableau *best10*, consisting only, for instance, of the **ten best-ranked alternatives**, with which we may compute a corresponding integer outranking digraph valued in the range (-1008, +1008).

```

1  >>> from cRandPerfTabs import cPartialPerformanceTableau
2  >>> best10 = cPartialPerformanceTableau(pt,qr.boostedRanking[:10])
3  >>> from cIntegerOutrankingDigraphs import *
4  >>> g = IntegerBipolarOutrankingDigraph(best10)
5  >>> g.valuationdomain
6  {'min': -1008, 'med': 0, 'max': 1008, 'hasIntegerValuation': True}
7  >>> g.showRelationTable(ReflexiveTerms=False)
8  * ---- Relation Table -----
9  r(x>y) | #773909 #668947 #567308 #578560 #426464 #298061 #155874
10  ↳#815552 #279729 #928564
11  ----- | -----
12  ↳-----+
13  #773909 | - +390 +90 +270 -50 +340 +220 □
14  ↳+60 +116 +222
15  #668947 | +78 - +42 +250 -22 +218 +56 □
16  ↳+172 +74 +64
17  #567308 | +70 +418 - +180 +156 +174 +266 □
18  ↳+78 +256 +306
19  #578560 | -4 +78 +28 - -12 +100 -48 □
20  ↳+154 -110 -10
21  #426464 | +202 +258 +284 +138 - +416 +312 □
22  ↳+382 +534 +278
23  #298061 | -48 +68 +172 +32 -42 - +54 □
24  ↳+48 +248 +374
25  #155874 | +72 +378 +322 +174 +274 +466 - □
26  ↳+212 +308 +418
27  #815552 | +78 +126 +272 +318 +54 +194 +172 - □
28  ↳-14 +22
29  #279729 | +240 +230 -110 +290 +72 +140 +388 □
30  ↳+62 - +250
31  #928564 | +22 +228 -14 +246 +36 +78 +56 □
32  ↳+110 +318 -
33  r(x>y) image range := [-1008;+1008]
34  >>> g.condorcetWinners()
35  [155874, 426464, 567308]
36  >>> g.computeChordlessCircuits()
37  []
38  >>> g.computeTransitivityDegree()
39  0.78

```

Three alternatives -#155874, #426464 and #567308- qualify as *Condorcet* winners, i.e. they each **positively outrank** all the other nine alternatives. No chordless outranking circuits are detected, yet the transitivity of the apparent outranking relation is not given. And, no clear ranking alignment hence appears when inspecting the *strict* outranking digraph (i.e. the codual $\sim(-g)$ of g) shown in Fig. 5.2.

```

1  >>> (~(-g)).exportGraphViz()

```

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```
2 *---- exporting a dot file for GraphViz tools -----*
3 Exporting to converse-dual_rel_best10.dot
4 dot -Tpng converse-dual_rel_best10.dot -o converse-dual_rel_best10.png
```

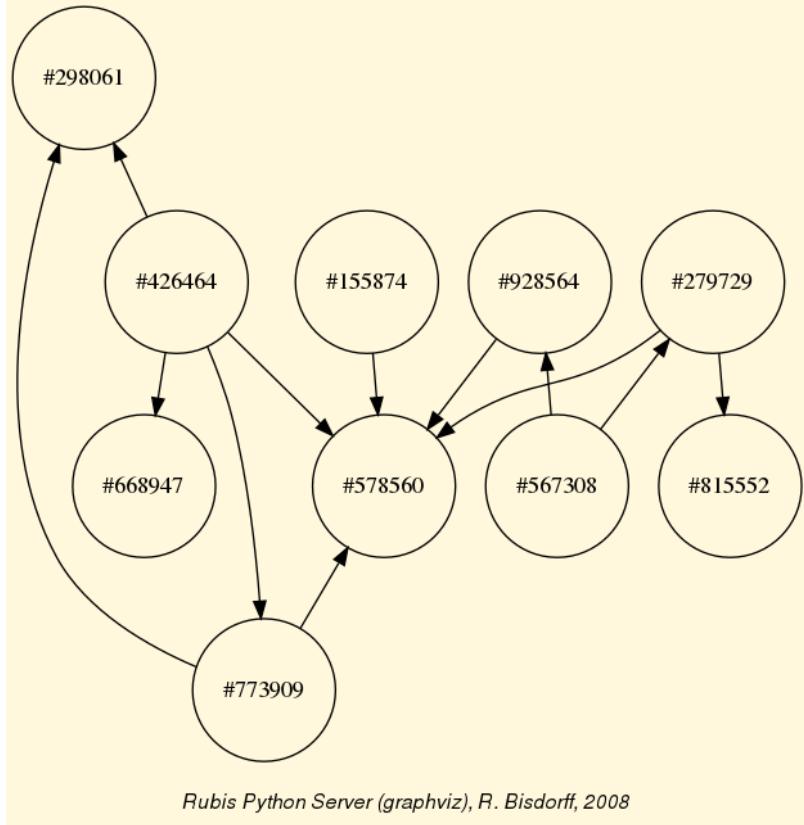


Fig. 5.2: Validated *strict* outranking situations between the ten best-ranked alternatives

Restricted to these ten best-ranked alternatives, the *Copeland*, the *NetFlows* as well as the *Kemeny* ranking rule will all rank alternative #426464 first and alternative #578560 last. Otherwise the three ranking rules produce in this case more or less different rankings.

```
1 >>> g.computeCopelandRanking()
2 [426464, 567308, 155874, 279729, 773909, 928564, 668947, 815552, 298061,
3   ↵ 578560]
4 >>> g.computeNetFlowsRanking()
5 [426464, 155874, 773909, 567308, 815552, 279729, 928564, 298061, 668947,
6   ↵ 578560]
7 >>> from linearOrders import KemenyOrder
8 >>> ke = KemenyOrder(g,orderLimit=10)
9 >>> ke.kemenyRanking
10 [426464, 773909, 155874, 815552, 567308, 298061, 928564, 279729, 668947,
11   ↵ 578560]
```

Note

It is therefore *important* to always keep in mind that, based on pairwise outranking situations, there **does not exist any unique optimal ranking**; especially when we face such big data problems. Changing the number of quantiles, the component ranking rule, the optimised quantile ordering strategy, all this will indeed produce, sometimes even substantially, diverse global ranking results.

5.3 On the MeluXina EuroHPC supercomputer (Summer 2024)⁵⁴

Summer 2024, the author was granted the opportunity to use HPC resources of the MeluXina EuroHPC supercomputer⁵⁵ (<https://www.luxprovide.lu/meluxina/>). Special big memory computing nodes on this HPC platform offer a large RAM for particularly demanding workloads. Each such node is composed of 2 AMD Rome CPUs (64 core @ 2.6 GHz, 256HT cores total), has 4 TB of memory (4096 GB) and 1.92 TB of local storage.

Following timings (see Table 5.1) could be achieved with a specially designed `cQuantilesRankingDigraphs` module⁵⁷ when q-tiling and ranking multiple incommensurable performance records of 21 criteria assessing three decision objectives, namely economic, environmental and societal aspects (see the *tutorial* (page 74) on generating random three-objectives performance tableaux).

Table 5.1: EuroHPC MeluXina Ranking Performance Records (Summer 2024)

digraph order	relation size	q	nbr of sorters	q-tiling time	nbr of compon.	nbr of rankers	tot.run time
1000000	1x10^12	7	100	30"	251468	48	1'07"
2000000	4x10^12	9	128	1'06"	313870	64	2'43"
3000000	9x10^12	7	128	1'44"	361401	64	4'20"
4000000	16x10^12	7	128	2'26"	389459	128	5'56"
5000000	25x10^12	7	128	3'05"	411422	84	8'35"
6000000	36x10^12	9	128	4'05"	439443	128	12'11"
7000000	49x10^12	7	128	4'48"	444444	128	15'06"
8000000	64x10^12	7	192	5'31"	457180	220	15'33"
9000000	81x10^12	7	192	6'02"	469127	220	18'40"
10000000	1x10^14	9	220	6'46"	500475	240	23'17"

One million records could be ranked with 100 sorting and 48 ranking multiprocessing threads in about 67 seconds. The quantiles sorting step is based on 7-tiling. Three

⁵⁴ The kind support of the *Faculty of Science Technology and Medecine* of the *University of Luxembourg* (<https://www.uni.lu/fstm-en/>) and of *LUXPROVIDE* (<https://www.luxprovide.lu/>) is gratefully acknowledged.

⁵⁵ The acquisition and operation of the EuroHPC supercomputer is funded jointly by the EuroHPC Joint Undertaking, through the European Union's Connecting Europe Facility and the Horizon 2020 research and innovation programme, as well as the Grand Duché du Luxembourg.

⁵⁷ The sources of the cythonized Digraph3 modules (with .pyx suffix) may be found in the *cython* directory of the Digraph3 resources.

million records could be ranked with 128 sorters and 64 rankers in 4 min. and 20 sec. and the quantiles sorting step is here again based on 7-tiling. With 128 sorters and 84 rankers, up to five million records could be 7-tiled and ranked in 8 min. and 35 sec.

Below is shown an example *MeluXina* session for ranking six million incommensurable performance records assessing 3 decision objectives concerning economic, environmental and societal aspects on 21 criteria⁵⁸. The Python 3.12.4 interpreter, compiled with GCC 8.5.0 RH and enabled optimizations, is running in a virtual environment on RH 8.5.0-20 Linux. All the cythonized modules were compiled with Cython-3.0.10 in the same environment. [Page 281, 57](#)

```

1 (MyPy3124) [userRB@mel4005 Digraph3]$ python3
2 Python 3.12.4 (main, Jul 19 2024, 15:25:25)
3 [GCC 8.5.0 20210514 (Red Hat 8.5.0-20)] on linux
4 Type "help", "copyright", "credits" or "license" for more information.
5 >>>

```

```

1 >>> from cRandPerfTabs import \
2 ...     cRandom3ObjectivesPerformanceTableau as cR3ObjPT
3 >>> pt = cR3ObjPT(numberOfActions=6000000,
4 ...                     numberOfCriteria=21,
5 ...                     weightDistribution='equiobjectives',
6 ...                     commonScale = (0.0,1000.0),
7 ...                     commonThresholds = [(1.5,0.0),(2.0,0.0),(75.0,0.0)],
8 ...                     commonMode = ['beta','variable',None],
9 ...                     missingDataProbability=0.05,
10 ...                     seed=16)
11 >>> import cQuantilesRankingDigraphs as QRD
12 >>> qr = QRD.cQuantilesRankingDigraph(pt,quantiles=9,
13 ...                                         quantilesOrderingStrategy='optimal',
14 ...                                         minimalComponentSize=1,
15 ...                                         componentRankingRule='Copeland',
16 ...                                         LowerClosed=False,
17 ...                                         Threading=True,
18 ...                                         nbrOfSorters=128,
19 ...                                         nbrOfRankers=128,
20 ...                                         tempDir='/project/scratch/userRB',
21 ...                                         Comments=False)
22 >>> qr
23 *----- Object instance description -----*
24 Instance class      : cQuantilesRankingDigraph
25 Instance name       : random3ObjectivesPerfTab_mp
26 Actions             : 6000000
27 Criteria            : 21
28 Sorting by          : 9-Tiling
29 Ordering strategy   : optimal

```

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⁵⁸ See the *tutorial* (page 74) on generating random three-objectives performance tableaux.

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```
30 Ranking rule      : Copeland
31 Components        : 439443
32 Minimal order    : 1
33 Maximal order    : 924
34 Average order    : 13.7
35 fill rate        : 0.001%
36 Attributes        : ['runTimes', 'name', 'actions', 'order',
37                         'dimension', 'sortingParameters', 'nbrOfSorters',
38                         'startMethod', 'valuationdomain', 'profiles',
39                         'categories', 'sorting', 'minimalComponentSize',
40                         'decomposition', 'nbrComponents', 'nd',
41                         'nbrOfRankers', 'components', 'fillRate',
42                         'maximalComponentSize', 'componentRankingRule',
43                         'boostedRanking']
44 ---- Constructor run times (in sec.) ----
45 Sorting threads   : 128
46 Ranking threads   : 128
47 StartMethod       : spawn
48 Total time        : 730.49080
49 Data input         : 104.95025
50 QuantilesSorting  : 245.87293
51 Preordering        : 21.06959
52 Components ranking: 354.03710
```

With 128 sorting threads and 128 ranking threads, we need about 12 min., 4 min. for the 9-tiling step and 7 min. for locally ranking each one of the 439443 components. The fill-rate of the resulting sparse outranking digraph is 0.001%.

Back to [Content Table](#) (page 1)

6 Moving on to undirected graphs

This last part of the tutorials introduces Python resources for working with undirected graphs.

- [Working with the *graphs* module](#) (page 284)
- [Computing the non isomorphic MISs of the 12-cycle graph](#) (page 296)
- [About comparability, split, interval and permutation graphs](#) (page 301)
- [On tree graphs and graph forests](#) (page 315)

6.1 Working with the graphs module

- *Structure of a Graph object* (page 284)
- *q-coloring of a graph* (page 287)
- *MIS and clique enumeration* (page 289)
- *Line graphs and maximal matchings* (page 290)
- *Grids and the Ising model* (page 293)
- *Simulating Metropolis random walks* (page 294)

Structure of a Graph object

In the **graphs** module, the root **Graph** class provides a generic **simple graph model**, without loops and multiple links. A given object of this class consists in:

1. the graph **vertices** : a dictionary of vertices with ‘name’ and ‘shortName’ attributes,
2. the graph **valuationDomain** , a dictionary with three entries: the minimum (-1, means certainly no link), the median (0, means missing information) and the maximum characteristic value (+1, means certainly a link),
3. the graph **edges** : a dictionary with frozensets of pairs of vertices as entries carrying a characteristic value in the range of the previous valuation domain,
4. and its associated **gamma function** : a dictionary containing the direct neighbors of each vertex, automatically added by the object constructor.

See the technical documentation of the **graphs** module.

Example Python3 session

```
1 >>> from graphs import Graph
2 >>> g = Graph(numberOfVertices=7, edgeProbability=0.5)
3 >>> g.save(fileName='tutorialGraph')
```

The saved **Graph** instance named ‘tutorialGraph.py’ is encoded in python3 as follows.

```
1 # Graph instance saved in Python format
2 vertices = {
3     'v1': {'shortName': 'v1', 'name': 'random vertex'},
4     'v2': {'shortName': 'v2', 'name': 'random vertex'},
5     'v3': {'shortName': 'v3', 'name': 'random vertex'},
6     'v4': {'shortName': 'v4', 'name': 'random vertex'},
7     'v5': {'shortName': 'v5', 'name': 'random vertex'},
8     'v6': {'shortName': 'v6', 'name': 'random vertex'},
9     'v7': {'shortName': 'v7', 'name': 'random vertex'},
```

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```
10 }
11 valuationDomain = {'min':-1,'med':0,'max':1}
12 edges = {
13     frozenset(['v1','v2']): -1,
14     frozenset(['v1','v3']): -1,
15     frozenset(['v1','v4']): -1,
16     frozenset(['v1','v5']): 1,
17     frozenset(['v1','v6']): -1,
18     frozenset(['v1','v7']): -1,
19     frozenset(['v2','v3']): 1,
20     frozenset(['v2','v4']): 1,
21     frozenset(['v2','v5']): -1,
22     frozenset(['v2','v6']): 1,
23     frozenset(['v2','v7']): -1,
24     frozenset(['v3','v4']): -1,
25     frozenset(['v3','v5']): -1,
26     frozenset(['v3','v6']): -1,
27     frozenset(['v3','v7']): -1,
28     frozenset(['v4','v5']): 1,
29     frozenset(['v4','v6']): -1,
30     frozenset(['v4','v7']): 1,
31     frozenset(['v5','v6']): 1,
32     frozenset(['v5','v7']): -1,
33     frozenset(['v6','v7']): -1,
34 }
```

The stored graph can be recalled and plotted with the generic `exportGraphViz()`^{Page 7, 1} method as follows.

```
1 >>> g = Graph('tutorialGraph')
2 >>> g.exportGraphViz()
3 *---- exporting a dot file for GraphViz tools -----*
4 Exporting to tutorialGraph.dot
5 fdp -Tpng tutorialGraph.dot -o tutorialGraph.png
```

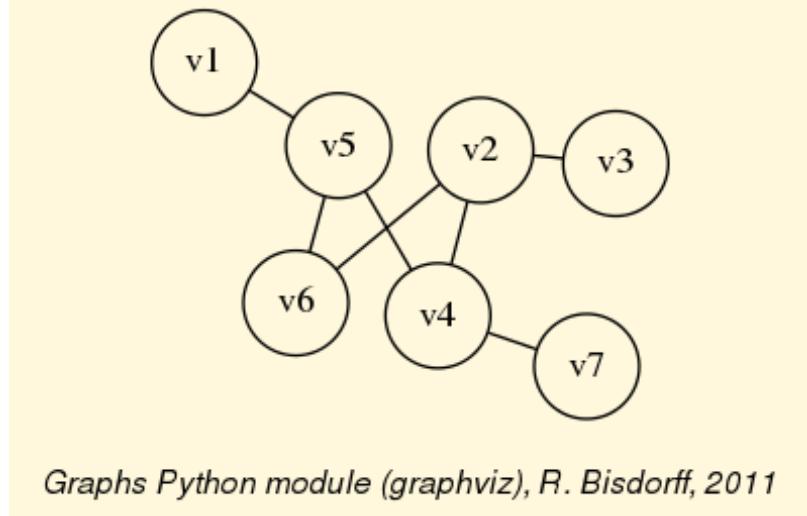


Fig. 6.1: Tutorial graph instance

Properties, like the gamma function and vertex degrees and neighbourhood depths may be shown with a *graphs.Graph.showShort()* method.

```

1 >>> g.showShort()
2 *---- short description of the graph ----*
3 Name           : 'tutorialGraph'
4 Vertices       : ['v1', 'v2', 'v3', 'v4', 'v5', 'v6', 'v7']
5 Valuation domain : {'min': -1, 'med': 0, 'max': 1}
6 Gamma function :
7   v1 -> ['v5']
8   v2 -> ['v6', 'v4', 'v3']
9   v3 -> ['v2']
10  v4 -> ['v5', 'v2', 'v7']
11  v5 -> ['v1', 'v6', 'v4']
12  v6 -> ['v2', 'v5']
13  v7 -> ['v4']
14  degrees      : [0, 1, 2, 3, 4, 5, 6]
15  distribution  : [0, 3, 1, 3, 0, 0, 0]
16  nbh depths   : [0, 1, 2, 3, 4, 5, 6, 'inf.']
17  distribution  : [0, 0, 1, 4, 2, 0, 0, 0]
```

A **Graph** instance corresponds bijectively to a symmetric **Digraph** instance and we may easily convert from one to the other with the **graph2Digraph()**, and vice versa with the **digraph2Graph()** method. Thus, all resources of the **Digraph** class, suitable for symmetric digraphs, become readily available, and vice versa.

```

1 >>> dg = g.graph2Digraph()
2 >>> dg.showRelationTable(ndigits=0,ReflexiveTerms=False)
3 * ---- Relation Table ----
4   S | 'v1'  'v2'  'v3'  'v4'  'v5'  'v6'  'v7'
5   ---|-----
```

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```

6   'v1' |   -   -1   -1   -1    1   -1   -1
7   'v2' |   -1   -   1    1   -1    1   -1
8   'v3' |   -1    1   -   -1   -1   -1   -1
9   'v4' |   -1    1   -1   -   1   -1    1
10  'v5' |    1   -1   -1    1   -   1   -1
11  'v6' |   -1    1   -1   -1    1   -   -1
12  'v7' |   -1   -1   -1    1   -1   -1   -
13 >>> g1 = dg.digraph2Graph()
14 >>> g1.showShort()
15 *---- short description of the graph ----*
16 Name          : 'tutorialGraph'
17 Vertices      : ['v1', 'v2', 'v3', 'v4', 'v5', 'v6', 'v7']
18 Valuation domain : {'med': 0, 'min': -1, 'max': 1}
19 Gamma function :
20 v1 -> ['v5']
21 v2 -> ['v3', 'v6', 'v4']
22 v3 -> ['v2']
23 v4 -> ['v5', 'v7', 'v2']
24 v5 -> ['v6', 'v1', 'v4']
25 v6 -> ['v5', 'v2']
26 v7 -> ['v4']
27 degrees       : [0, 1, 2, 3, 4, 5, 6]
28 distribution  : [0, 3, 1, 3, 0, 0, 0]
29 nbh depths   : [0, 1, 2, 3, 4, 5, 6, 'inf.']
30 distribution  : [0, 0, 1, 4, 2, 0, 0, 0]
```

q-coloring of a graph

A 3-coloring of the tutorial graph g may for instance be computed and plotted with the `Q_Coloring` class as follows.

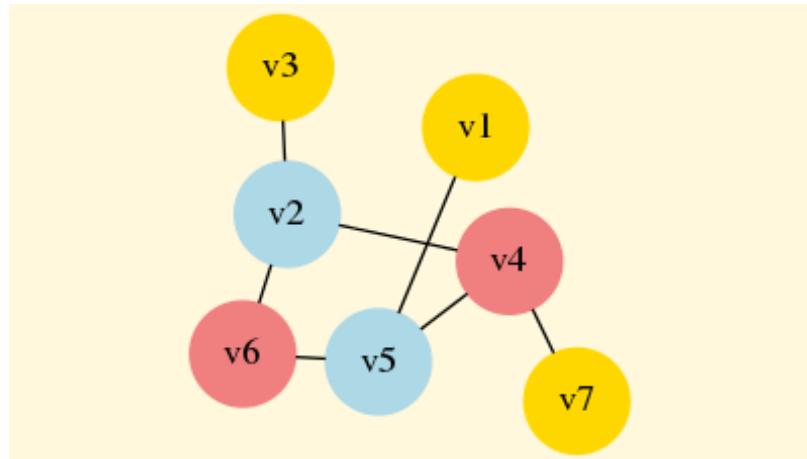
```

1 >>> from graphs import Q_Coloring
2 >>> qc = Q_Coloring(g)
3 Running a Gibbs Sampler for 42 step !
4 The q-coloring with 3 colors is feasible !!
5 >>> qc.showConfiguration()
6 v5 lightblue
7 v3 gold
8 v7 gold
9 v2 lightblue
10 v4 lightcoral
11 v1 gold
12 v6 lightcoral
13 >>> qc.exportGraphViz('tutorial-3-coloring')
14 *---- exporting a dot file for GraphViz tools -----
15 Exporting to tutorial-3-coloring.dot
```

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```
16 fdp -Tpng tutorial-3-coloring.dot -o tutorial-3-coloring.png
```



Graphs Python module (graphviz), R. Bisdorff, 2014

Fig. 6.2: 3-Coloring of the tutorial graph

Actually, with the given tutorial graph instance, a 2-coloring is already feasible.

```
1 >>> qc = Q_Coloring(g,colors=['gold','coral'])
2   Running a Gibbs Sampler for 42 step !
3   The q-coloring with 2 colors is feasible !!
4 >>> qc.showConfiguration()
5   v5 gold
6   v3 coral
7   v7 gold
8   v2 gold
9   v4 coral
10  v1 coral
11  v6 coral
12 >>> qc.exportGraphViz('tutorial-2-coloring')
13   Exporting to tutorial-2-coloring.dot
14   fdp -Tpng tutorial-2-coloring.dot -o tutorial-2-coloring.png
```

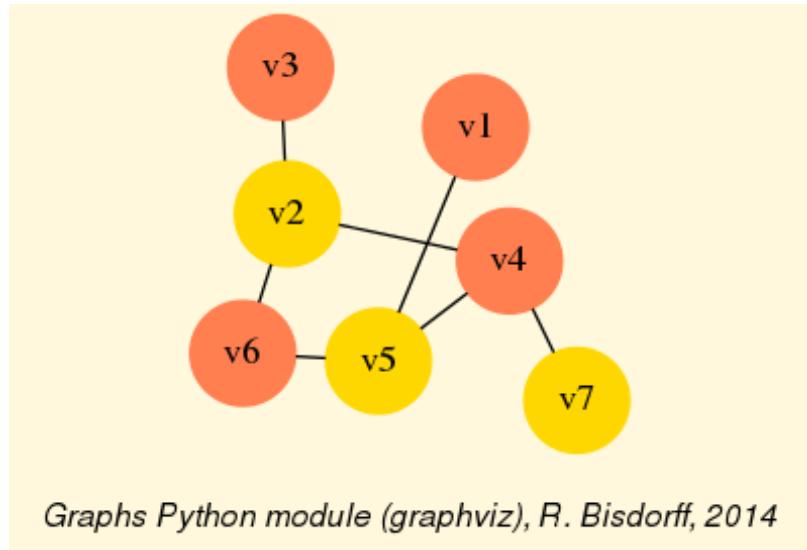


Fig. 6.3: 2-coloring of the tutorial graph

MIS and clique enumeration

2-colorings define independent sets of vertices that are maximal in cardinality; for short called a **MIS**. Computing such MISs in a given `Graph` instance may be achieved by the `showMIS()` method.

```

1  >>> g = Graph('tutorialGraph')
2  >>> g.showMIS()
3  *--- Maximal Independent Sets ---*
4  ['v2', 'v5', 'v7']
5  ['v3', 'v5', 'v7']
6  ['v1', 'v2', 'v7']
7  ['v1', 'v3', 'v6', 'v7']
8  ['v1', 'v3', 'v4', 'v6']
9  number of solutions: 5
10 cardinality distribution
11 card.: [0, 1, 2, 3, 4, 5, 6, 7]
12 freq.: [0, 0, 0, 3, 2, 0, 0, 0]
13 execution time: 0.00032 sec.
14 Results in self.misset
15 >>> g.misset
16 [frozenset({'v7', 'v2', 'v5'}),
17  frozenset({'v3', 'v7', 'v5'}),
18  frozenset({'v1', 'v2', 'v7'}),
19  frozenset({'v1', 'v6', 'v7', 'v3'}),
20  frozenset({'v1', 'v6', 'v4', 'v3'})]
```

A MIS in the dual of a graph instance g (its negation $-g$ ^{Page 18, 14}), corresponds to a maximal **clique**, i.e. a maximal complete subgraph in g . Maximal cliques may be directly enumerated with the `showCliques()` method.

```

1  >>> g.showCliques()
2  *--- Maximal Cliques ---*
3  ['v2', 'v3']
4  ['v4', 'v7']
5  ['v2', 'v4']
6  ['v4', 'v5']
7  ['v1', 'v5']
8  ['v2', 'v6']
9  ['v5', 'v6']
10 number of solutions: 7
11 cardinality distribution
12 card.: [0, 1, 2, 3, 4, 5, 6, 7]
13 freq.: [0, 0, 7, 0, 0, 0, 0, 0]
14 execution time: 0.00049 sec.
15 Results in self.cliques
16 >>> g.cliques
17 [frozenset({'v2', 'v3'}), frozenset({'v4', 'v7'}),
18 frozenset({'v2', 'v4'}), frozenset({'v4', 'v5'}),
19 frozenset({'v1', 'v5'}), frozenset({'v6', 'v2'}),
20 frozenset({'v6', 'v5'})]
```

Line graphs and maximal matchings

The module also provides a `LineGraph` constructor. A **line graph** represents the **adjacencies between edges** of the given graph instance. We may compute for instance the line graph of the 5-cycle graph.

```

1  >>> from graphs import CycleGraph, LineGraph
2  >>> g = CycleGraph(order=5)
3  >>> g
4  *----- Graph instance description -----
5  Instance class   : CycleGraph
6  Instance name    : cycleGraph
7  Graph Order      : 5
8  Graph Size       : 5
9  Valuation domain : [-1.00; 1.00]
10 Attributes       : ['name', 'order', 'vertices', 'valuationDomain',
11                      'edges', 'size', 'gamma']
12 >>> lg = LineGraph(g)
13 >>> lg
14 *----- Graph instance description -----
15 Instance class   : LineGraph
16 Instance name    : line-cycleGraph
17 Graph Order      : 5
18 Graph Size       : 5
19 Valuation domain : [-1.00; 1.00]
20 Attributes       : ['name', 'graph', 'valuationDomain', 'vertices',
```

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```

21             'order', 'edges', 'size', 'gamma']
22 >>> lg.showShort()
23     ----- short description of the graph -----
24     Name           : 'line-cycleGraph'
25     Vertices       : [frozenset({'v1', 'v2'}), frozenset({'v1', 'v5'}), ↳
26     ↪frozenset({'v2', 'v3'}),                                ↳
27     ↪frozenset({'v3', 'v4'}), frozenset({'v4', 'v5'})]
28     Valuation domain : {'min': Decimal('-1'), 'med': Decimal('0'), 'max': ↳
29     ↪Decimal('1')}
30     Gamma function   :
31     frozenset({'v1', 'v2'}) -> [frozenset({'v2', 'v3'}), frozenset({'v1',
32     ↪'v5'})]
33     frozenset({'v1', 'v5'}) -> [frozenset({'v1', 'v2'}), frozenset({'v4',
34     ↪'v5'})]
35     frozenset({'v2', 'v3'}) -> [frozenset({'v1', 'v2'}), frozenset({'v3',
36     ↪'v4'})]
37     frozenset({'v3', 'v4'}) -> [frozenset({'v2', 'v3'}), frozenset({'v4',
38     ↪'v5'})]
39     frozenset({'v4', 'v5'}) -> [frozenset({'v4', 'v3'}), frozenset({'v1',
40     ↪'v5'})]
41     degrees         : [0, 1, 2, 3, 4]
42     distribution    : [0, 0, 5, 0, 0]
43     nbh depths     : [0, 1, 2, 3, 4, 'inf.']
44     distribution    : [0, 0, 5, 0, 0]

```

Iterated line graph constructions are usually expanding, except for *chordless cycles*, where the same cycle is repeated, and for *non-closed paths*, where iterated line graphs progressively reduce one by one the number of vertices and edges and become eventually an empty graph.

Notice that the MISs in the line graph provide **maximal matchings** - *maximal sets of independent edges* - of the original graph.

```

1 >>> c8 = CycleGraph(order=8)
2 >>> lc8 = LineGraph(c8)
3 >>> lc8.showMIS()
4     ----- Maximal Independent Sets -----
5     [frozenset({'v3', 'v4'}), frozenset({'v5', 'v6'}), frozenset({'v1', 'v8
6     ↪'})]
7     [frozenset({'v2', 'v3'}), frozenset({'v5', 'v6'}), frozenset({'v1', 'v8
8     ↪'})]
9     [frozenset({'v8', 'v7'}), frozenset({'v2', 'v3'}), frozenset({'v5', 'v6
10    ↪'})]
11    [frozenset({'v8', 'v7'}), frozenset({'v2', 'v3'}), frozenset({'v4', 'v5
12    ↪'})]
13    [frozenset({'v7', 'v6'}), frozenset({'v3', 'v4'}), frozenset({'v1', 'v8
14    ↪'})]

```

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```

10 [frozenset({'v2', 'v1'}), frozenset({'v8', 'v7'}), frozenset({'v4', 'v5
11   ↪'})]
12 [frozenset({'v2', 'v1'}), frozenset({'v7', 'v6'}), frozenset({'v4', 'v5
13   ↪'})]
14 [frozenset({'v2', 'v1'}), frozenset({'v7', 'v6'}), frozenset({'v3', 'v4
15   ↪'})]
16 [frozenset({'v7', 'v6'}), frozenset({'v2', 'v3'}), frozenset({'v1', 'v8
17   ↪'})],
18   frozenset({'v4', 'v5'})]
19 [frozenset({'v2', 'v1'}), frozenset({'v8', 'v7'}), frozenset({'v3', 'v4
20   ↪'})],
21   frozenset({'v5', 'v6'})]
number of solutions: 10
cardinality distribution
card.: [0, 1, 2, 3, 4, 5, 6, 7, 8]
freq.: [0, 0, 0, 8, 2, 0, 0, 0, 0]
execution time: 0.00029 sec.

```

The two last MIs of cardinality 4 (see Lines 13-16 above) give **isomorphic perfect maximum matchings** of the 8-cycle graph. Every vertex of the cycle is adjacent to a matching edge. Odd cycle graphs do not admit any perfect matching.

```

1 >>> maxMatching = c8.computeMaximumMatching()
2 >>> c8.exportGraphViz(fileName='maxMatchingcycleGraph',
3 ...                               matching=maxMatching)
4 ----- exporting a dot file for GraphViz tools -----
5 Exporting to maxMatchingcycleGraph.dot
6 Matching: {frozenset({'v1', 'v2'}), frozenset({'v5', 'v6'}),
7           frozenset({'v3', 'v4'}), frozenset({'v7', 'v8'}) }
8 circo -Tpng maxMatchingcycleGraph.dot -o maxMatchingcycleGraph.png

```

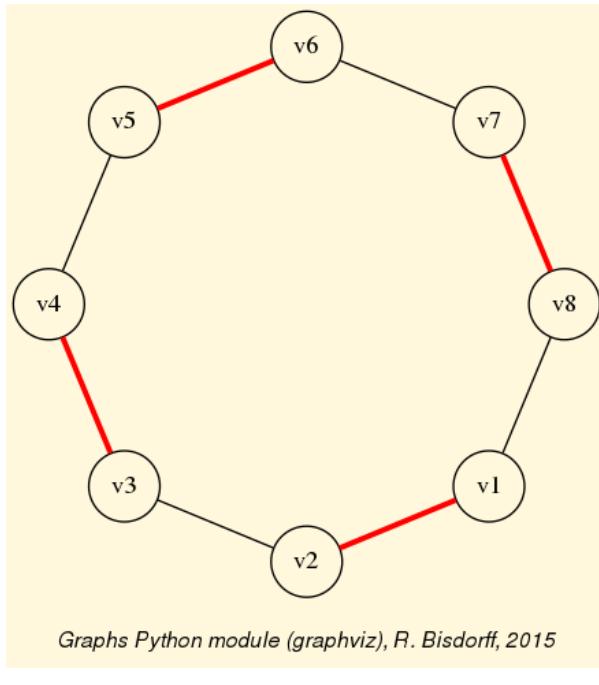


Fig. 6.4: A perfect maximum matching of the 8-cycle graph

Grids and the Ising model

Special classes of graphs, like $n \times m$ **rectangular** or **triangular grids** (`GridGraph` and `IsingModel`) are available in the `graphs` module. For instance, we may use a Gibbs sampler again for simulating an **Ising Model** on such a grid.

```

1 >>> from graphs import GridGraph, IsingModel
2 >>> g = GridGraph(n=15,m=15)
3 >>> g.showShort()
4     *----- show short -----*
5     Grid graph      : grid-6-6
6     n              : 6
7     m              : 6
8     order          : 36
9 >>> im = IsingModel(g,beta=0.3,nSim=100000,Debug=False)
10    Running a Gibbs Sampler for 100000 step !
11 >>> im.exportGraphViz(colors=['lightblue','lightcoral'])
12     *----- exporting a dot file for GraphViz tools -----*
13     Exporting to grid-15-15-ising.dot
14     fdp -Tpng grid-15-15-ising.dot -o grid-15-15-ising.png

```

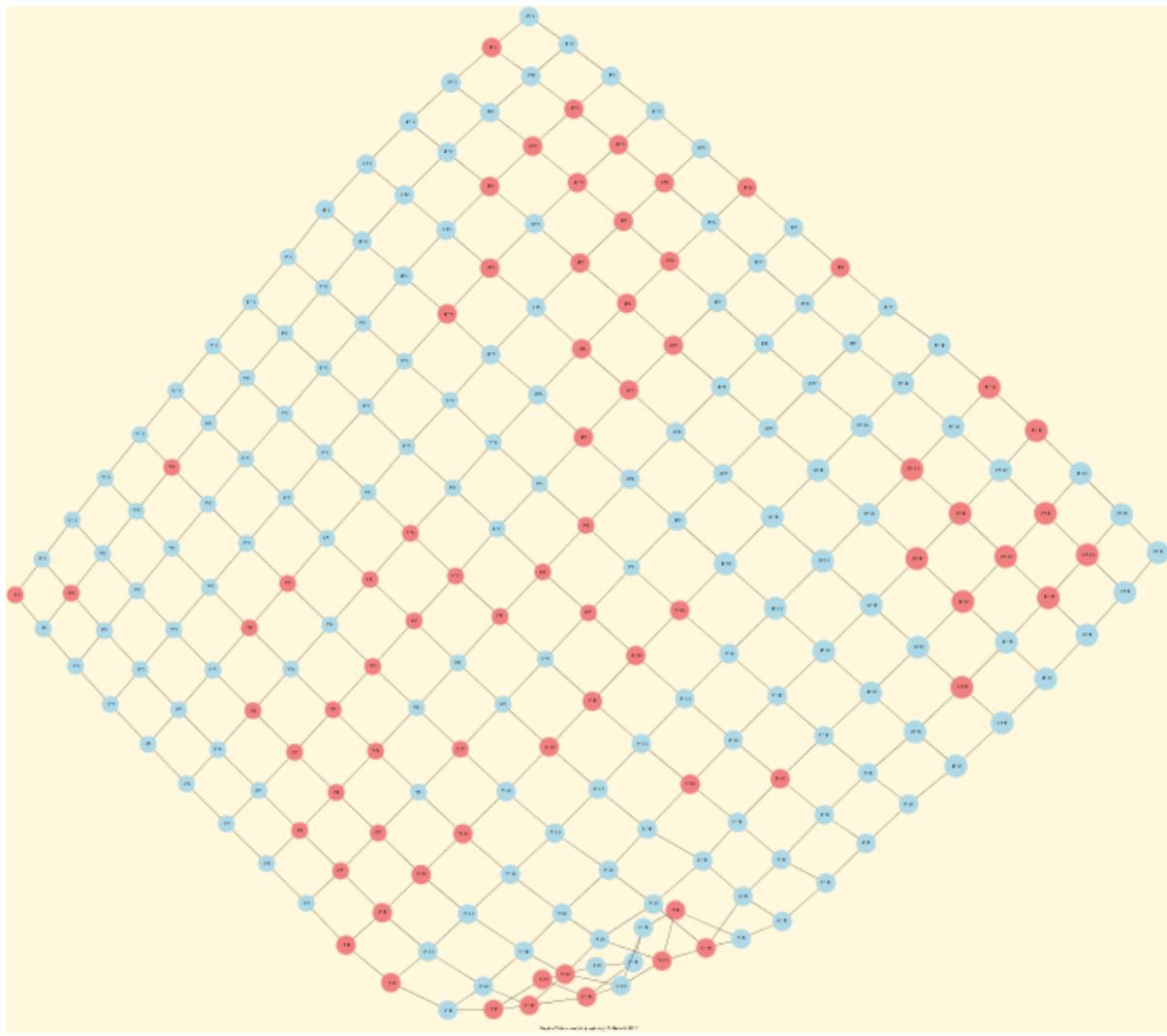


Fig. 6.5: Ising model of the 15x15 grid graph

Simulating Metropolis random walks

Finally, we provide the `MetropolisChain` class, a specialization of the `Graph` class, for implementing a generic **Metropolis MCMC** (Monte Carlo Markov Chain) sampler for simulating random walks on a given graph following a given probability $probs = \{‘v1’: x, ‘v2’: y, …\}$ for visiting each vertex (see Lines 14-22).

```

1 >>> from graphs import MetropolisChain
2 >>> g = Graph(numberOfVertices=5, edgeProbability=0.5)
3 >>> g.showShort()
4     ----- short description of the graph -----
5     Name          : 'randomGraph'
6     Vertices      : ['v1', 'v2', 'v3', 'v4', 'v5']
7     Valuation domain : {'max': 1, 'med': 0, 'min': -1}
8     Gamma function :
9     v1 -> ['v2', 'v3', 'v4']
10    v2 -> ['v1', 'v4']

```

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```
11 v3 -> ['v5', 'v1']
12 v4 -> ['v2', 'v5', 'v1']
13 v5 -> ['v3', 'v4']
```

```
1 >>> probs = {} # initialize a potential stationary probability vector
2 >>> n = g.order # for instance: probs[v_i] = n-i/Sum(1:n) for i in 1:n
3 >>> i = 0
4 >>> verticesList = [x for x in g.vertices]
5 >>> verticesList.sort()
6 >>> for v in verticesList:
7 ...     probs[v] = (n - i)/(n*(n+1)/2)
8 ...     i += 1
```

The `checkSampling()` method (see Line 23) generates a random walk of $nSim=30000$ steps on the given graph and records by the way the observed relative frequency with which each vertex is passed by.

```
1 >>> met = MetropolisChain(g,probs)
2 >>> frequency = met.checkSampling(verticesList[0],nSim=30000)
3 >>> for v in verticesList:
4 ...     print(v,probs[v],frequency[v])
5
6 v1 0.3333 0.3343
7 v2 0.2666 0.2680
8 v3 0.2 0.2030
9 v4 0.1333 0.1311
10 v5 0.0666 0.0635
```

In this example, the stationary transition probability distribution, shown by the `showTransitionMatrix()` method above (see below), is quite adequately simulated.

```
1 >>> met.showTransitionMatrix()
2 * ---- Transition Matrix -----
3   Pij | 'v1'    'v2'    'v3'    'v4'    'v5'
4   -----|-----
5   'v1' |  0.23    0.33    0.30    0.13    0.00
6   'v2' |  0.42    0.42    0.00    0.17    0.00
7   'v3' |  0.50    0.00    0.33    0.00    0.17
8   'v4' |  0.33    0.33    0.00    0.08    0.25
9   'v5' |  0.00    0.00    0.50    0.50    0.00
```

For more technical information and more code examples, look into the technical documentation of the graphs module. For the readers interested in algorithmic applications of Markov Chains we may recommend consulting O. Häggström's 2002 book: [FMCAA].

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6.2 Computing the non isomorphic MISs of the 12-cycle graph

- *Introduction* (page 296)
- *Computing the maximal independent sets (MISs)* (page 297)
- *Computing the automorphism group* (page 299)
- *Computing the isomorphic MISs* (page 299)

Introduction

Due to the public success of our common 2008 publication with Jean-Luc Marichal [ISOMIS-08] , we present in this tutorial an example Python session for computing the **non isomorphic maximal independent sets** (MISs) from the 12-cycle graph, i.e. a CirculantDigraph class instance of order 12 and symmetric circulants 1 and -1.

```
1 >>> from digraphs import CirculantDigraph
2 >>> c12 = CirculantDigraph(order=12,circulants=[1,-1])
3 >>> c12 # 12-cycle digraph instance
4 ----- Digraph instance description -----
5 Instance class      : CirculantDigraph
6 Instance name       : c12
7 Digraph Order       : 12
8 Digraph Size        : 24
9 Valuation domain   : [-1.0, 1.0]
10 Determinateness    : 100.000
11 Attributes         : ['name', 'order', 'circulants', 'actions',
12                           'valuationdomain', 'relation', 'gamma',
13                           'notGamma']
```

Such n -cycle graphs are also provided as undirected graph instances by the CycleGraph class.

```
1 >>> from graphs import CycleGraph
2 >>> cg12 = CycleGraph(order=12)
3 >>> cg12
4 ----- Graph instance description -----
5 Instance class      : CycleGraph
6 Instance name       : cycleGraph
7 Graph Order         : 12
8 Graph Size          : 12
9 Valuation domain   : [-1.0, 1.0]
10 Attributes         : ['name', 'order', 'vertices', 'valuationDomain',
11                           'edges', 'size', 'gamma']
12 >>> cg12.exportGraphViz('cg12')
```

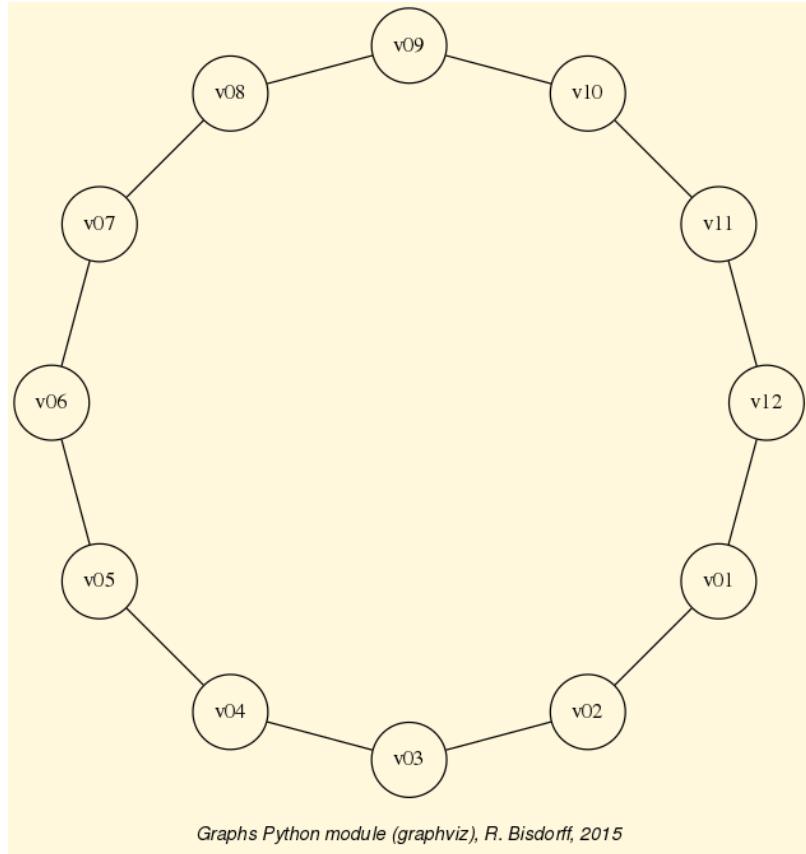


Fig. 6.6: The 12-cycle graph

Computing the maximal independent sets (MISs)

A non isomorphic MIS corresponds in fact to a set of isomorphic MISs, i.e. an orbit of MISs under the automorphism group of the 12-cycle graph. We are now first computing all maximal independent sets that are detectable in the 12-cycle digraph with the `showMIS()` method.

```

1 >>> c12.showMIS(withListing=False)
2     *--- Maximal independent choices ---*
3     number of solutions:  29
4     cardinality distribution
5     card.: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12]
6     freq.: [0, 0, 0, 0, 3, 24, 2, 0, 0, 0, 0, 0]
7     Results in c12.misset

```

In the 12-cycle graph, we observe 29 labelled MISs: – 3 of cardinality 4, 24 of cardinality 5, and 2 of cardinality 6. In case of n -cycle graphs with $n > 20$, as the cardinality of the MISs becomes big, it is preferable to use the shell `perrinMIS` command compiled from C and installed³ along with all the Digraphs3 python modules for computing the set of

³ The `perrinMIS` shell command may be installed system wide with the command `.../Digraph3$ make installPerrin` from the main Digraph3 directory. It is stored by default into `</usr/local/bin/>`. This may be changed with the `INSTALLDIR` flag. The command `.../Digraph3$ make installPerrinUser` installs it instead without sudo into the user's private `<$Home/.bin>` directory.

MISs observed in the graph.

```
1 ...$ echo 12 | /usr/local/bin/perrinMIS
2 # ----- #
3 # Generating MIS set of Cn with the #
4 # Perrin sequence algorithm. #
5 # Temporary files used. #
6 # even versus odd order optimised. #
7 # RB December 2006 #
8 # Current revision Dec 2018 #
9 #
10 Input cycle order ? <-- 12
11 mis 1 : 100100100100
12 mis 2 : 010010010010
13 mis 3 : 001001001001
14 ...
15 ...
16 ...
17 mis 27 : 001001010101
18 mis 28 : 101010101010
19 mis 29 : 010101010101
20 Cardinalities:
21 0 : 0
22 1 : 0
23 2 : 0
24 3 : 0
25 4 : 3
26 5 : 24
27 6 : 2
28 7 : 0
29 8 : 0
30 9 : 0
31 10 : 0
32 11 : 0
33 12 : 0
34 Total: 29
35 execution time: 0 sec. and 2 millisec.
```

Reading in the result of the *perrinMIS* shell command, stored in a file called by default ‘curd.dat’, may be operated with the `readPerrinMisset()` method.

```
1 >>> c12.readPerrinMisset(file='curd.dat')
2 >>> c12.misset
3 {frozenset({'5', '7', '10', '1', '3'}),
4  frozenset({'9', '11', '5', '2', '7'}),
5  frozenset({'7', '2', '4', '10', '12'}),
6  ...
7  ...}
```

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```

8 ...
9   frozenset({'8', '4', '10', '1', '6'}),
10  frozenset({'11', '4', '1', '9', '6'}),
11  frozenset({'8', '2', '4', '10', '12', '6'})
12 }
```

Computing the automorphism group

For computing the corresponding non isomorphic MISs, we actually need the automorphism group of the c12-cycle graph. The `Digraph` class therefore provides the `automorphismGenerators()` method which adds automorphism group generators to a `Digraph` class instance with the help of the external shell `dreadnaut` command from the `nauty` software package².

```

1 >>> c12.automorphismGenerators()
2 ...
3 Permutations
4 {'1': '1', '2': '12', '3': '11', '4': '10', '5':
5   '9', '6': '8', '7': '7', '8': '6', '9': '5', '10':
6   '4', '11': '3', '12': '2'}
7 {'1': '2', '2': '1', '3': '12', '4': '11', '5': '10',
8   '6': '9', '7': '8', '8': '7', '9': '6', '10': '5',
9   '11': '4', '12': '3'}
10 >>> print('grpsize = ', c12.automorphismGroupSize)
11 grpsize = 24
```

The 12-cycle graph automorphism group is generated with both the permutations above and has group size 24.

Computing the isomorphic MISs

The command `showOrbits()` renders now the labelled representatives of each of the four orbits of isomorphic MISs observed in the 12-cycle graph (see Lines 7-10).

```

1 >>> c12.showOrbits(c12.misset, withListing=False)
2 ...
3 ----- Global result -----
4 Number of MIS: 29
5 Number of orbits : 4
6 Labelled representatives and cardinality:
7 1: ['2', '4', '6', '8', '10', '12'], 2
8 2: ['2', '5', '8', '11'], 3
9 3: ['2', '4', '6', '9', '11'], 12
```

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² Dependency: The `automorphismGenerators()` method uses the shell `dreadnaut` command from the `nauty` software package. See <https://www3.cs.stonybrook.edu/~algorith/implement/nauty/implement.shtml>. On Mac OS there exist dmg installers and on Ubuntu Linux or Debian, one may easily install it with `...$ sudo apt-get install nauty`.

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```

10 4: ['1','4','7','9','11'], 12
11 Symmetry vector
12 stabilizer size: [1, 2, 3, ..., 8, 9, ..., 12, 13, ...]
13 frequency : [0, 2, 0, ..., 1, 0, ..., 1, 0, ...]

```

The corresponding group stabilizers' sizes and frequencies – orbit 1 with 6 symmetry axes, orbit 2 with 4 symmetry axes, and orbits 3 and 4 both with one symmetry axis (see Lines 12-13), are illustrated in the corresponding unlabelled graphs of Fig. 6.7 below.

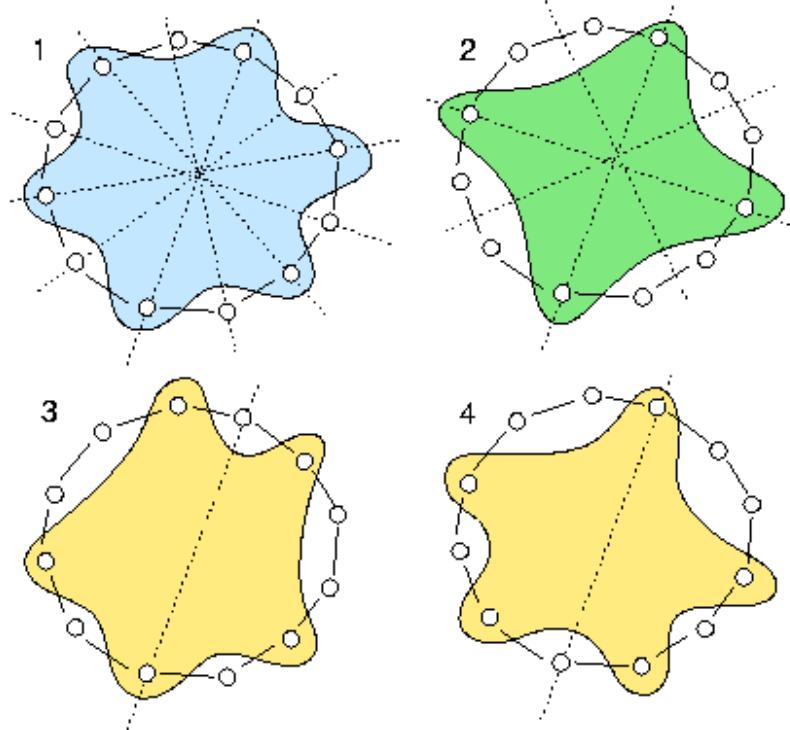


Fig. 6.7: The symmetry axes of the four non isomorphic MISs of the 12-cycle graph

The non isomorphic MISs in the 12-cycle graph represent in fact all the ways one may write the number 12 as the circular sum of '2's and '3's without distinguishing opposite directions of writing. The first orbit corresponds to writing six times a '2'; the second orbit corresponds to writing four times a '3'. The third and fourth orbit correspond to writing two times a '3' and three times a '2'. There are two non isomorphic ways to do this latter circular sum. Either separating the '3's by one and two '2's, or by zero and three '2's (see Bisdorff & Marichal [ISOMIS-08]).

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6.3 About comparability, split, interval and permutation graphs

- *A multiply perfect graph* (page 301)
- *Who is the liar ?* (page 303)
- *Generating permutation graphs* (page 306)
- *Recognizing permutation graphs* (page 309)

A multiply *perfect* graph

A graph g is called:

- **Berge** or **perfect** when g and its dual $-g$ both don't contain any chordless odd cycles of length greater than 3 ([BER-1963], [CHU-2006]),
- **Triangulated** when g does not contain any chordless cycle of length 4 and more.

Following Martin Golumbic (see [GOL-2004] p. 149), we call a given graph g :

- **Comparability graph** when g is *transitively orientable*;
- **Interval graph** when g is *triangulated* and its dual $-g$ is a *comparability* graph;
- **Permutation graph** when g and its dual $-g$ are both *comparability* graphs;
- **Split graph** when g and its dual $-g$ are both *triangulated* graphs.

All these four kinds of graphs are in fact *perfect* graphs. To illustrate these graph classes, we generate from 8 intervals, randomly chosen in the default integer range $[0,10]$, a `RandomIntervalIntersectionsGraph` instance g (see Listing 6.1 Line 2 below).

Listing 6.1: A multiply perfect random interval intersection graph

```
1  >>> from graphs import RandomIntervalIntersectionsGraph
2  >>> g = RandomIntervalIntersectionsGraph(order=8, seed=100)
3  >>> g
4  *----- Graph instance description -----*
5  Instance class    : RandomIntervalIntersectionsGraph
6  Instance name     : randIntervalIntersections
7  Seed              : 100
8  Graph Order       : 8
9  Graph Size        : 23
10 Valuation domain : [-1.0; 1.0]
11 Attributes        : ['seed', 'name', 'order', 'intervals',
12                         'vertices', 'valuationDomain',
13                         'edges', 'size', 'gamma']
14 >>> print(g.intervals)
15 [(2, 7), (2, 7), (5, 6), (6, 8), (1, 8), (1, 1), (4, 7), (0, 10)]
```

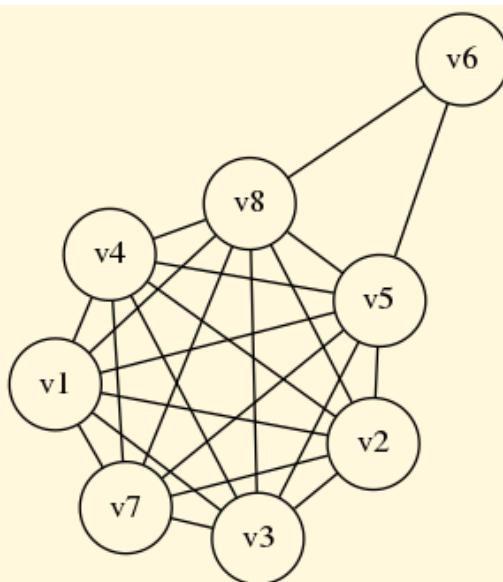
With seed = 100, we obtain here an *interval* graph, in fact a *perfect* graph g , which is **conjointly** a *triangulated*, a *comparability*, a *split* and a *permutation* graph (see Listing 6.2 Lines 6,10,14).

Listing 6.2: testing perfect graph categories

```

1  >>> g.isPerfectGraph(Comments=True)
2  Graph randIntervalIntersections is perfect !
3  >>> g.isIntervalGraph(Comments=True)
4  Graph 'randIntervalIntersections' is triangulated.
5  Graph 'dual_randIntervalIntersections' is transitively orientable.
6  => Graph 'randIntervalIntersections' is an interval graph.
7  >>> g.isSplitGraph(Comments=True)
8  Graph 'randIntervalIntersections' is triangulated.
9  Graph 'dual_randIntervalIntersections' is triangulated.
10 => Graph 'randIntervalIntersections' is a split graph.
11 >>> g.isPermutationGraph(Comments=True)
12 Graph 'randIntervalIntersections' is transitively orientable.
13 Graph 'dual_randIntervalIntersections' is transitively orientable.
14 => Graph 'randIntervalIntersections' is a permutation graph.
15 >>> print(g.computePermutation())
16 ['v5', 'v6', 'v4', 'v2', 'v1', 'v3', 'v7', 'v8']
17 ['v8', 'v6', 'v1', 'v2', 'v3', 'v4', 'v7', 'v5']
18 [8, 2, 6, 5, 7, 4, 3, 1]
19 >>> g.exportGraphViz('randomSplitGraph')
20 *---- exporting a dot file for GraphViz tools -----*
21 Exporting to randomSplitGraph.dot
22 fdp -Tpng randomSplitGraph.dot -o randomSplitGraph.png

```



Graphs Python module (graphviz), R. Bisdorff, 2019

Fig. 6.8: A conjointly triangulated, comparability, interval, permutation and split graph

In Fig. 6.8 we may readily recognize the essential characteristic of **split graphs**, namely being always splitable into two disjoint sub-graphs: an *independent choice* $\{v6\}$ and a *clique* $\{v1, v2, v3, v4, v5, v7, v8\}$; which explains their name.

Notice however that the four properties:

1. g is a *comparability* graph;
2. g is a *cocomparability* graph, i.e. $-g$ is a *comparability* graph;
3. g is a *triangulated* graph;
4. g is a *cotriangulated* graph, i.e. $-g$ is a *comparability* graph;

are *independent* of one another (see [GOL-2004] p. 275).

Who is the liar ?

Claude Berge's famous mystery story (see [GOL-2004] p.20) may well illustrate the importance of being an **interval graph**.

Suppose that the file ‘berge.py’¹⁸ contains the following **Graph** instance data:

```

1 vertices = {
2   'A': {'name': 'Abe', 'shortName': 'A'},
3   'B': {'name': 'Burt', 'shortName': 'B'},
4   'C': {'name': 'Charlotte', 'shortName': 'C'},
5   'D': {'name': 'Desmond', 'shortName': 'D'},
6   'E': {'name': 'Eddie', 'shortName': 'E'},
7   'I': {'name': 'Ida', 'shortName': 'I'},
8 }
9 valuationDomain = {'min':-1,'med':0,'max':1}
10 edges = {
11   frozenset(['A','B']): 1,
12   frozenset(['A','C']): -1,
13   frozenset(['A','D']): 1,
14   frozenset(['A','E']): 1,
15   frozenset(['A','I']): -1,
16   frozenset(['B','C']): -1,
17   frozenset(['B','D']): -1,
18   frozenset(['B','E']): 1,
19   frozenset(['B','I']): 1,
20   frozenset(['C','D']): 1,
21   frozenset(['C','E']): 1,
22   frozenset(['C','I']): 1,
23   frozenset(['D','E']): -1,
24   frozenset(['D','I']): 1,
25   frozenset(['E','I']): 1,
26 }
```

¹⁸ A Digraph3 *graphs.Graph* encoded file is available in the `examples` directory of the Digraph3 software collection.

Six professors (labeled A , B , C , D , E and I) had been to the library on the day that a rare document was stolen. Each entered once, stayed for some time, and then left. If two professors were in the library at the same time, then at least one of them saw the other. Detectives questioned the professors and gathered the testimonies that A saw B and E ; B saw A and I ; C saw D and I ; D saw A and I ; E saw B and I ; and I saw C and E . This data is gathered in the previous file, where each positive edge $\{x, y\}$ models the testimony that, either x saw y , or y saw x .

```

1 >>> from graphs import Graph
2 >>> g = Graph('berge')
3 >>> g.showShort()
4     ----- short description of the graph -----
5 Name           : 'berge'
6 Vertices       : ['A', 'B', 'C', 'D', 'E', 'I']
7 Valuation domain : {'min': -1, 'med': 0, 'max': 1}
8 Gamma function :
9 A -> ['D', 'B', 'E']
10 B -> ['E', 'I', 'A']
11 C -> ['E', 'D', 'I']
12 D -> ['C', 'I', 'A']
13 E -> ['C', 'B', 'I', 'A']
14 I -> ['C', 'E', 'B', 'D']
15 >>> g.exportGraphViz('berge1')
16     ----- exporting a dot file for GraphViz tools -----
17 Exporting to berge1.dot
18 fdp -Tpng berge1.dot -o berge1.png

```

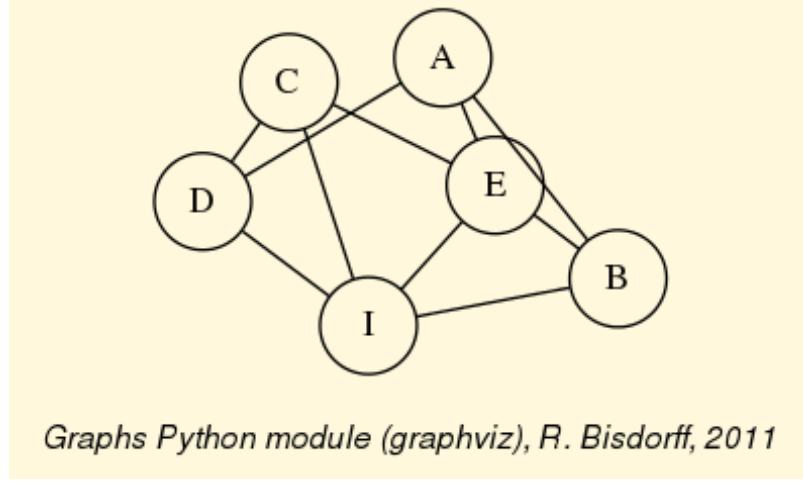


Fig. 6.9: Graph representation of the testimonies of the professors

From graph theory we know that time interval intersections graphs must in fact be interval graphs, i.e. *triangulated* and *co-comparative* graphs. The testimonies graph should therefore not contain any chordless cycle of four and more vertices. Now, the presence or not of such chordless cycles in the testimonies graph may be checked as follows.

```

1 >>> g.computeChordlessCycles()
2 Chordless cycle certificate -->>> ['D', 'C', 'E', 'A', 'D']
3 Chordless cycle certificate -->>> ['D', 'I', 'E', 'A', 'D']
4 Chordless cycle certificate -->>> ['D', 'I', 'B', 'A', 'D']
5 ([['D', 'C', 'E', 'A', 'D'], frozenset({'C', 'D', 'E', 'A'})),
6 ([['D', 'I', 'E', 'A', 'D'], frozenset({'D', 'E', 'I', 'A'})),
7 ([['D', 'I', 'B', 'A', 'D'], frozenset({'D', 'B', 'I', 'A'})])

```

We see three intersection cycles of length 4, which is impossible to occur on the linear time line. Obviously one professor lied!

And it is D ; if we put to doubt his testimony that he saw A (see Line 1 below), we obtain indeed a *triangulated* graph instance whose dual is a *comparability* graph.

```

1 >>> g.setEdgeValue( ('D', 'A'), 0)
2 >>> g.showShort()
3     ----- short description of the graph -----
4 Name           : 'berge'
5 Vertices       : ['A', 'B', 'C', 'D', 'E', 'I']
6 Valuation domain : {'med': 0, 'min': -1, 'max': 1}
7 Gamma function :
8 A -> ['B', 'E']
9 B -> ['A', 'I', 'E']
10 C -> ['I', 'E', 'D']
11 D -> ['I', 'C']
12 E -> ['A', 'I', 'B', 'C']
13 I -> ['B', 'E', 'D', 'C']
14 >>> g.isIntervalGraph(Comments=True)
15 Graph 'berge' is triangulated.
16 Graph 'dual_berge' is transitively orientable.
17 => Graph 'berge' is an interval graph.
18 >>> g.exportGraphViz('berge2')
19     ----- exporting a dot file for GraphViz tools -----
20 Exporting to berge2.dot
21 fdp -Tpng berge2.dot -o berge2.png

```

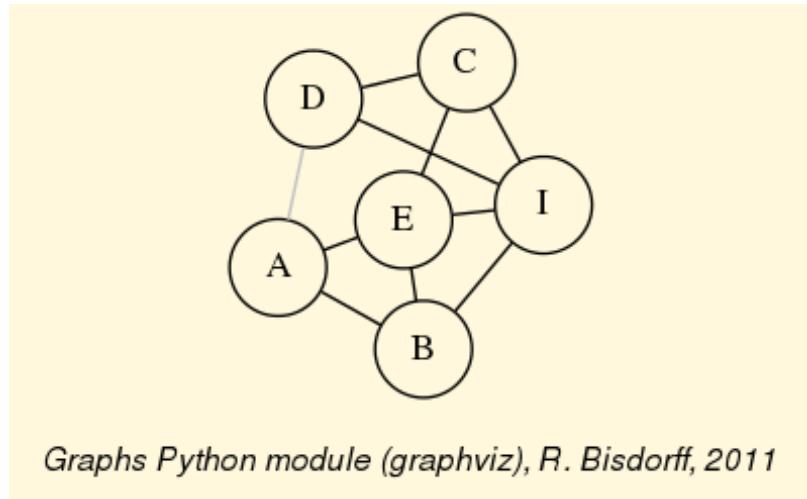


Fig. 6.10: The triangulated testimonies graph

Generating permutation graphs

A graph is called a **permutation** or *inversion* graph if there exists a permutation of its list of vertices such that the graph is isomorphic to the inversions operated by the permutation in this list (see [GOL-2004] Chapter 7, pp 157-170). This kind is also part of the class of perfect graphs.

```

1  >>> from graphs import PermutationGraph
2  >>> g = PermutationGraph(permuation = [4, 3, 6, 1, 5, 2])
3  >>> g
4  *----- Graph instance description -----*
5  Instance class    : PermutationGraph
6  Instance name     : permutationGraph
7  Graph Order       : 6
8  Permutation       : [4, 3, 6, 1, 5, 2]
9  Graph Size        : 9
10 Valuation domain : [-1.00; 1.00]
11 Attributes        : ['name', 'vertices', 'order', 'permuation',
12                           'valuationDomain', 'edges', 'size', 'gamma']
13 >>> g.isPerfectGraph()
14 True
15 >>> g.exportGraphViz()
16 *---- exporting a dot file for GraphViz tools -----*
17 Exporting to permutationGraph.dot
18 fdp -Tpng permutationGraph.dot -o permutationGraph.png

```

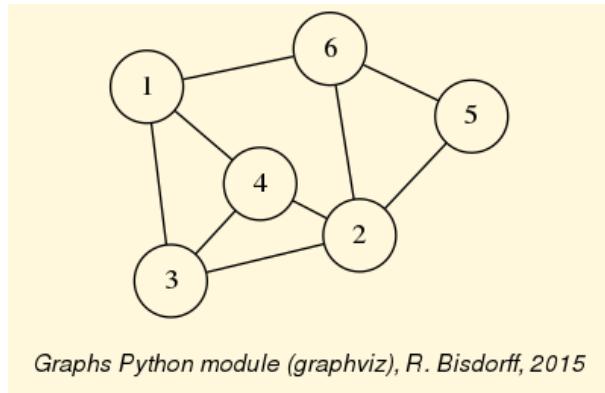


Fig. 6.11: The default permutation graph

By using color sorting queues, the minimal vertex coloring for a permutation graph is computable in $O(n \log(n))$ (see [GOL-2004]).

```

1 >>> g.computeMinimalVertexColoring(Comments=True)
2   vertex 1: lightcoral
3   vertex 2: lightcoral
4   vertex 3: lightblue
5   vertex 4: gold
6   vertex 5: lightblue
7   vertex 6: gold
8 >>> g.exportGraphViz(fileName='coloredPermutationGraph',
9 ...           WithVertexColoring=True)
10 *----- exporting a dot file for GraphViz tools -----*
11 Exporting to coloredPermutationGraph.dot
12 fdp -Tpng coloredPermutationGraph.dot -o coloredPermutationGraph.png

```

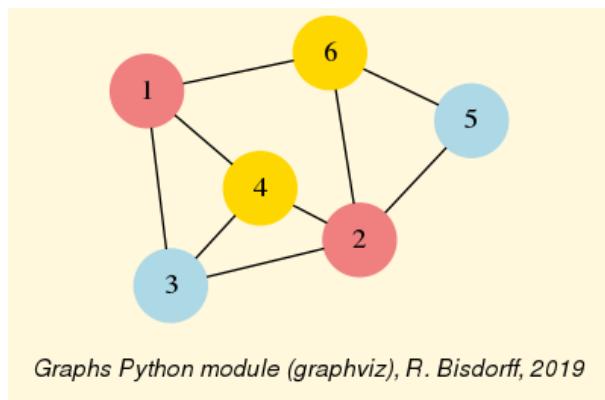


Fig. 6.12: Minimal vertex coloring of the permutation graph

The correspondingly colored **matching diagram** of the nine **inversions** -the actual *edges* of the permutation graph-, which are induced by the given permutation $[4, 3, 6, 1, 5, 2]$, may as well be drawn with the graphviz *neato* layout and explicitly positioned horizontal lists of vertices (see Fig. 6.13).

```

1 >>> g.exportPermutationGraphViz(WithEdgeColoring=True)
2 ----- exporting a dot file for GraphViz tools -----
3 Exporting to perm_permutationGraph.dot
4 neato -n -Tpng perm_permutationGraph.dot -o perm_permutationGraph.png

```

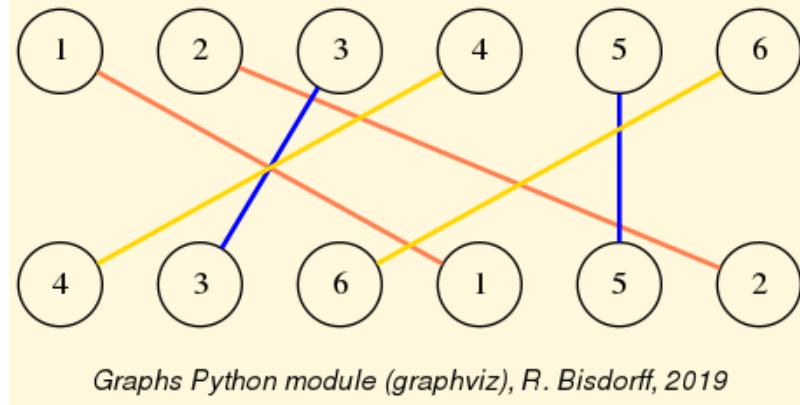


Fig. 6.13: Colored matching diagram of the permutation [4, 3, 6, 1, 5, 2]

As mentioned before, a permutation graph and its dual are **transitively orientable**. The `transitiveOrientation()` method constructs from a given permutation graph a digraph where each edge of the permutation graph is converted into an arc oriented in increasing alphabetic order of the adjacent vertices' keys (see [GOL-2004]). This orientation of the edges of a permutation graph is always transitive and delivers a *transitive ordering* of the vertices.

```

1 >>> dg = g.transitiveOrientation()
2 >>> dg
3 ----- Digraph instance description -----
4 Instance class   : TransitiveDigraph
5 Instance name    : oriented_permutationGraph
6 Digraph Order    : 6
7 Digraph Size     : 9
8 Valuation domain : [-1.00; 1.00]
9 Determinateness  : 100.000
10 Attributes       : ['name', 'order', 'actions', 'valuationdomain',
11                                'relation', 'gamma', 'notGamma', 'size']
12 >>> print('Transitivity degree: %.3f' % dg.computeTransitivityDegree() )
13 Transitivity degree: 1.000
14 >>> dg.exportGraphViz()
15 ----- exporting a dot file for GraphViz tools -----
16 Exporting to oriented_permutationGraph.dot
17 0 subgraph { rank = same; 1; 2; }
18 1 subgraph { rank = same; 5; 3; }
19 2 subgraph { rank = same; 4; 6; }
20 dot -Grankdir=TB -Tpng oriented_permutationGraph.dot -o oriented_
→ permutationGraph.png

```

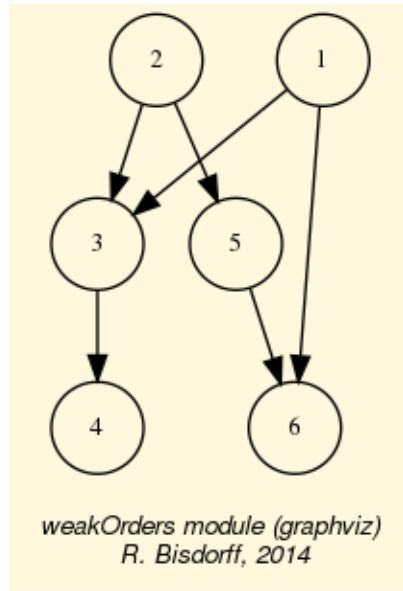


Fig. 6.14: Hasse diagram of the transitive orientation of the permutation graph

The dual of a permutation graph is *again* a permutation graph and as such also transitively orientable.

```

1 >>> dgd = (-g).transitiveOrientation()
2 >>> print('Dual transitivity degree: %.3f' %\
3 ...     dgd.computeTransitivityDegree() )
4
5 Dual transitivity degree: 1.000

```

Recognizing permutation graphs

Now, a given graph g is a **permutation graph** if and only if both g and $-g$ are *transitively orientable*. This property gives a polynomial test procedure (in $O(n^3)$ due to the transitivity check) for recognizing permutation graphs.

Let us consider, for instance, the following random graph of *order* 8 generated with an *edge probability* of 40% and a *random seed* equal to 4335.

```

1 >>> from graphs import RandomGraph
2 >>> g = RandomGraph(order=8, edgeProbability=0.4, seed=4335)
3 >>> g
4 *----- Graph instance description -----*
5 Instance class    : RandomGraph
6 Instance name     : randomGraph
7 Seed              : 4335
8 Edge probability  : 0.4
9 Graph Order      : 8
10 Graph Size       : 10
11 Valuation domain : [-1.00; 1.00]
12 Attributes       : ['name', 'order', 'vertices', 'valuationDomain',
(continues on next page)

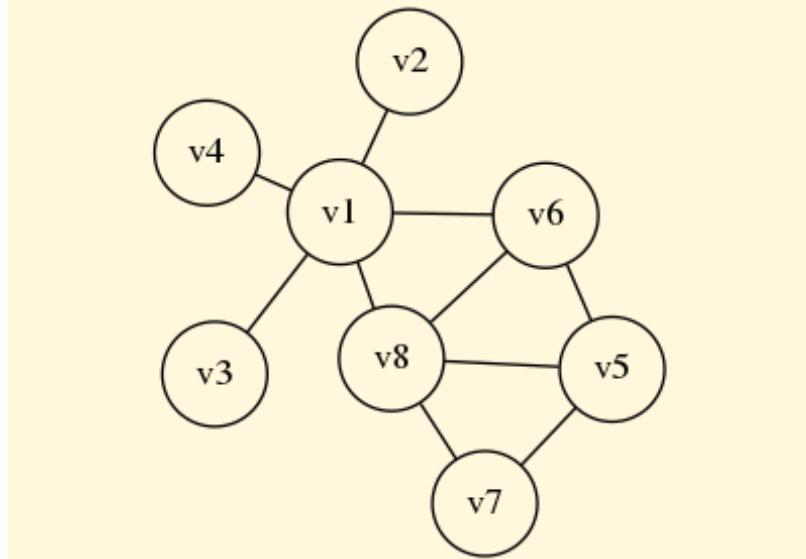
```

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```

13         'seed', 'edges', 'size',
14         'gamma', 'edgeProbability']
15 >>> g.isPerfectGraph()
16 True
17 >>> g.exportGraphViz()

```



Graphs Python module (graphviz), R. Bisdorff, 2015

Fig. 6.15: Random graph of order 8 generated with edge probability 0.4

If the random perfect graph instance g (see Fig. 6.15) is indeed a permutation graph, g and its dual $-g$ should be *transitively orientable*, i.e. **comparability graphs** (see [GOL-2004]). With the `isComparabilityGraph()` test, we may easily check this fact. This method proceeds indeed by trying to construct a transitive neighbourhood decomposition of a given graph instance and, if successful, stores the resulting edge orientations into a `self.edgeOrientations` attribute (see [GOL-2004] p.129-132).

```

1 >>> if g.isComparabilityGraph():
2     ...     print(g.edgeOrientations)
3
4 {('v1', 'v1'): 0, ('v1', 'v2'): 1, ('v2', 'v1'): -1, ('v1', 'v3'): 1,
5   ('v3', 'v1'): -1, ('v1', 'v4'): 1, ('v4', 'v1'): -1, ('v1', 'v5'): 0,
6   ('v5', 'v1'): 0, ('v1', 'v6'): 1, ('v6', 'v1'): -1, ('v1', 'v7'): 0,
7   ('v7', 'v1'): 0, ('v1', 'v8'): 1, ('v8', 'v1'): -1, ('v2', 'v2'): 0,
8   ('v2', 'v3'): 0, ('v3', 'v2'): 0, ('v2', 'v4'): 0, ('v4', 'v2'): 0,
9   ('v2', 'v5'): 0, ('v5', 'v2'): 0, ('v2', 'v6'): 0, ('v6', 'v2'): 0,
10  ('v2', 'v7'): 0, ('v7', 'v2'): 0, ('v2', 'v8'): 0, ('v8', 'v2'): 0,
11  ('v3', 'v3'): 0, ('v3', 'v4'): 0, ('v4', 'v3'): 0, ('v3', 'v5'): 0,
12  ('v5', 'v3'): 0, ('v3', 'v6'): 0, ('v6', 'v3'): 0, ('v3', 'v7'): 0,
13  ('v7', 'v3'): 0, ('v3', 'v8'): 0, ('v8', 'v3'): 0, ('v4', 'v4'): 0,

```

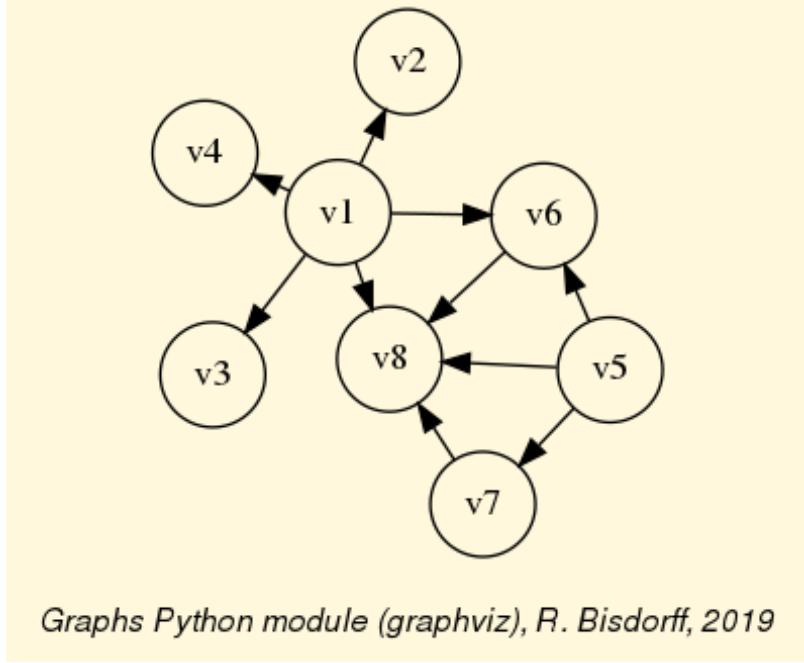
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```

14     ('v4', 'v5'): 0, ('v5', 'v4'): 0, ('v4', 'v6'): 0, ('v6', 'v4'): 0,
15     ('v4', 'v7'): 0, ('v7', 'v4'): 0, ('v4', 'v8'): 0, ('v8', 'v4'): 0,
16     ('v5', 'v5'): 0, ('v5', 'v6'): 1, ('v6', 'v5'): -1, ('v5', 'v7'): 1,
17     ('v7', 'v5'): -1, ('v5', 'v8'): 1, ('v8', 'v5'): -1, ('v6', 'v6'): 0,
18     ('v6', 'v7'): 0, ('v7', 'v6'): 0, ('v6', 'v8'): 1, ('v8', 'v6'): -1,
19     ('v7', 'v7'): 0, ('v7', 'v8'): 1, ('v8', 'v7'): -1, ('v8', 'v8'): 0}

```



Graphs Python module (graphviz), R. Bisdorff, 2019

Fig. 6.16: Transitive neighbourhoods of the graph g

The resulting orientation of the edges of g (see Fig. 6.16) is indeed transitive. The same procedure applied to the dual graph $gd = -g$ gives a transitive orientation to the edges of $-g$.

```

1 >>> gd = -g
2 >>> if gd.isComparabilityGraph():
3 ...     print(gd.edgeOrientations)
4
5 {('v1', 'v1'): 0, ('v1', 'v2'): 0, ('v2', 'v1'): 0, ('v1', 'v3'): 0,
6   ('v3', 'v1'): 0, ('v1', 'v4'): 0, ('v4', 'v1'): 0, ('v1', 'v5'): 1,
7   ('v5', 'v1'): -1, ('v1', 'v6'): 0, ('v6', 'v1'): 0, ('v1', 'v7'): 1,
8   ('v7', 'v1'): -1, ('v1', 'v8'): 0, ('v8', 'v1'): 0, ('v2', 'v2'): 0,
9   ('v2', 'v3'): -2, ('v3', 'v2'): 2, ('v2', 'v4'): -3, ('v4', 'v2'): 3,
10  ('v2', 'v5'): 1, ('v5', 'v2'): -1, ('v2', 'v6'): 1, ('v6', 'v2'): -1,
11  ('v2', 'v7'): 1, ('v7', 'v2'): -1, ('v2', 'v8'): 1, ('v8', 'v2'): -1,
12  ('v3', 'v3'): 0, ('v3', 'v4'): -3, ('v4', 'v3'): 3, ('v3', 'v5'): 1,
13  ('v5', 'v3'): -1, ('v3', 'v6'): 1, ('v6', 'v3'): -1, ('v3', 'v7'): 1,
14  ('v7', 'v3'): -1, ('v3', 'v8'): 1, ('v8', 'v3'): -1, ('v4', 'v4'): 0,
15  ('v4', 'v5'): 1, ('v5', 'v4'): -1, ('v4', 'v6'): 1, ('v6', 'v4'): -1,

```

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```

16    ('v4', 'v7'): 1, ('v7', 'v4'): -1, ('v4', 'v8'): 1, ('v8', 'v4'): -1,
17    ('v5', 'v5'): 0, ('v5', 'v6'): 0, ('v6', 'v5'): 0, ('v5', 'v7'): 0,
18    ('v7', 'v5'): 0, ('v5', 'v8'): 0, ('v8', 'v5'): 0, ('v6', 'v6'): 0,
19    ('v6', 'v7'): 1, ('v7', 'v6'): -1, ('v6', 'v8'): 0, ('v8', 'v6'): 0,
20    ('v7', 'v7'): 0, ('v7', 'v8'): 0, ('v8', 'v7'): 0, ('v8', 'v8'): 0}

```

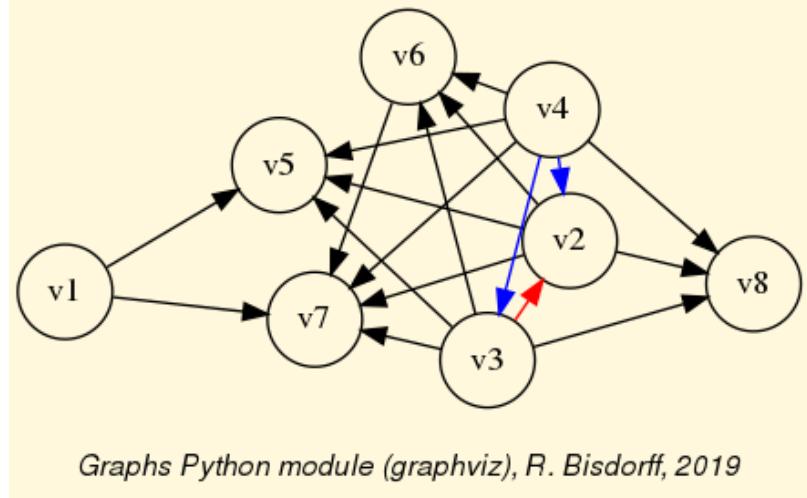


Fig. 6.17: Transitive neighbourhoods of the dual graph $-g$

It is worthwhile noticing that the orientation of g is achieved with a *single neighbourhood* decomposition, covering all the vertices. Whereas, the orientation of the dual $-g$ needs a decomposition into *three subsequent neighbourhoods* marked in black, red and blue (see Fig. 6.17).

Let us recheck these facts by explicitly constructing transitively oriented digraph instances with the `computeTransitivelyOrientedDigraph()` method.

```

1 >>> og = g.computeTransitivelyOrientedDigraph(PartiallyDetermined=True)
2 >>> print('Transitivity degree: %.3f' % (og.transitivityDegree))
3   Transitivity degree: 1.000
4 >>> ogd = (-g).
5   >>> computeTransitivelyOrientedDigraph(PartiallyDetermined=True)
6 >>> print('Transitivity degree: %.3f' % (ogd.transitivityDegree))
7   Transitivity degree: 1.000

```

The `PartiallyDetermined=True` flag (see Lines 1 and 4) is required here in order to orient *only* the actual edges of the graphs. Relations between vertices not linked by an edge will be put to the *indeterminate* characteristic value 0. This will allow us to compute, later on, convenient *disjunctive digraph fusions*.

As both graphs are indeed *transitively orientable* (see Lines 3 and 6 above), we may conclude that the given random graph g is actually a *permutation graph* instance. Yet, we still need to find now its corresponding *permutation*. We therefore implement a recipe given by Martin Golumbic [GOL-2004] p.159.

We will first **fuse** both *og* and *ogd* orientations above with an **epistemic disjunction** (see the `omax()` operator), hence, the partially determined orientations requested above.

Listing 6.3: Fusing graph orientations

```

1 >>> from digraphs import FusionDigraph
2 >>> f1 = FusionDigraph(og,ogd,operator='o-max')
3 >>> s1 = f1.computeCopelandRanking()
4 >>> print(s1)
5 ['v5', 'v7', 'v1', 'v6', 'v8', 'v4', 'v3', 'v2']

```

We obtain by the *Copeland* ranking rule (see tutorial on *ranking with incommensurable criteria* (page 82) and the `computeCopelandRanking()` method) a linear ordering of the vertices (see Listing 6.3 Line 5 above).

We reverse now the orientation of the edges in *og* (see *-og* in Line 1 below) in order to generate, again by *disjunctive fusion*, the *inversions* that are produced by the permutation we are looking for. Computing again a ranking with the *Copeland* rule, will show the correspondingly permuted list of vertices (see Line 4 below).

```

1 >>> f2 = FusionDigraph((-og),ogd,operator='o-max')
2 >>> s2 = f2.computeCopelandRanking()
3 >>> print(s2)
4 ['v8', 'v7', 'v6', 'v5', 'v4', 'v3', 'v2', 'v1']

```

Vertex *v8* is put from position 5 to position 1, vertex *v7* is put from position 2 to position 2, vertex *v6* from position 4 to position 3, vertex *v5* from position 1 to position 4, etc We generate these position swaps for all vertices and obtain thus the required permutation (see Line 5 below).

```

1 >>> permutation = [0 for j in range(g.order)]
2 >>> for j in range(g.order):
3 ...     permutation[s2.index(s1[j])] = j+1
4
5 >>> print(permutation)
6 [5, 2, 4, 1, 6, 7, 8, 3]

```

It is worthwhile noticing by the way that *transitive orientations* of a given graph and its dual are usually **not unique** and, so may also be the resulting permutations. However, they all correspond to isomorphic graphs (see [GOL-2004]). In our case here, we observe two different permutations and their reverses:

```

1 s1: ['v1', 'v4', 'v3', 'v2', 'v5', 'v6', 'v7', 'v8']
2 s2: ['v4', 'v3', 'v2', 'v8', 'v6', 'v1', 'v7', 'v5']
3 (s1 -> s2): [2, 3, 4, 8, 6, 1, 7, 5]
4 (s2 -> s1): [6, 1, 2, 3, 8, 5, 7, 4]

```

And:

```

1 s3: ['v5', 'v7', 'v1', 'v6', 'v8', 'v4', 'v3', 'v2']
2 s4: ['v8', 'v7', 'v6', 'v5', 'v4', 'v3', 'v2', 'v1']
3 (s3 -> s4): [5, 2, 4, 1, 6, 7, 8, 3]
4 (s4 -> s3) = [4, 2, 8, 3, 1, 5, 6, 7]

```

The `computePermutation()` method does directly operate all these steps: - computing transitive orientations, - ranking their epistemic fusion and, - delivering a corresponding permutation.

```

1 >>> g.computePermutation(Comments=True)
2 ['v1', 'v2', 'v3', 'v4', 'v5', 'v6', 'v7', 'v8']
3 ['v2', 'v3', 'v4', 'v8', 'v6', 'v1', 'v7', 'v5']
4 [2, 3, 4, 8, 6, 1, 7, 5]

```

We may finally check that, for instance, the two permutations $[2, 3, 4, 8, 6, 1, 7, 5]$ and $[4, 2, 8, 3, 1, 5, 6, 7]$ observed above, will correctly generate corresponding *isomorphic permutation* graphs.

```

1 >>> gtesta = PermutationGraph(permuation=[2, 3, 4, 8, 6, 1, 7, 5])
2 >>> gtestb = PermutationGraph(permuation=[4, 2, 8, 3, 1, 5, 6, 7])
3 >>> gtesta.exportGraphViz('gtesta')
4 >>> gtestb.exportGraphViz('gtestb')

```

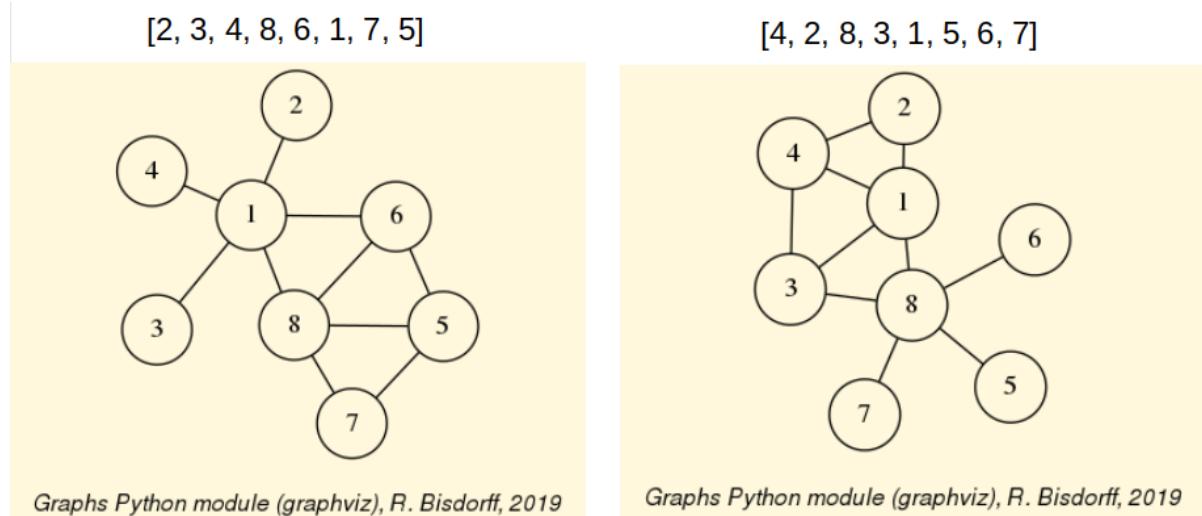


Fig. 6.18: Isomorphic permutation graphs

And, we recover indeed two *isomorphic copies* of the original random graph (compare Fig. 6.18 with Fig. 6.15).

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6.4 On tree graphs and graph forests

- *Generating random tree graphs* (page 315)
- *Recognizing tree graphs* (page 318)
- *Spanning trees and forests* (page 320)
- *Maximum determined spanning forests* (page 322)

Generating random tree graphs

Using the `RandomTree` class, we may, for instance, generate a random tree graph with 9 vertices.

```
1 >>> from graphs import RandomTree
2 >>> t = RandomTree(order=9, seed=100)
3 >>> t
4     ----- Graph instance description -----
5 Instance class    : RandomTree
6 Instance name     : randomTree
7 Graph Order       : 9
8 Graph Size        : 8
9 Valuation domain  : [-1.00; 1.00]
10 Attributes        : ['name', 'order', 'vertices', 'valuationDomain',
11                         'edges', 'prueferCode', 'size', 'gamma']
12     ----- RandomTree specific data -----
13 Prüfer code   : ['v3', 'v8', 'v8', 'v3', 'v7', 'v6', 'v7']
14 >>> t.exportGraphViz('tutRandomTree')
15     ----- exporting a dot file for GraphViz tools -----
16 Exporting to tutRandomTree.dot
17 neato -Tpng tutRandomTree.dot -o tutRandomTree.png
```

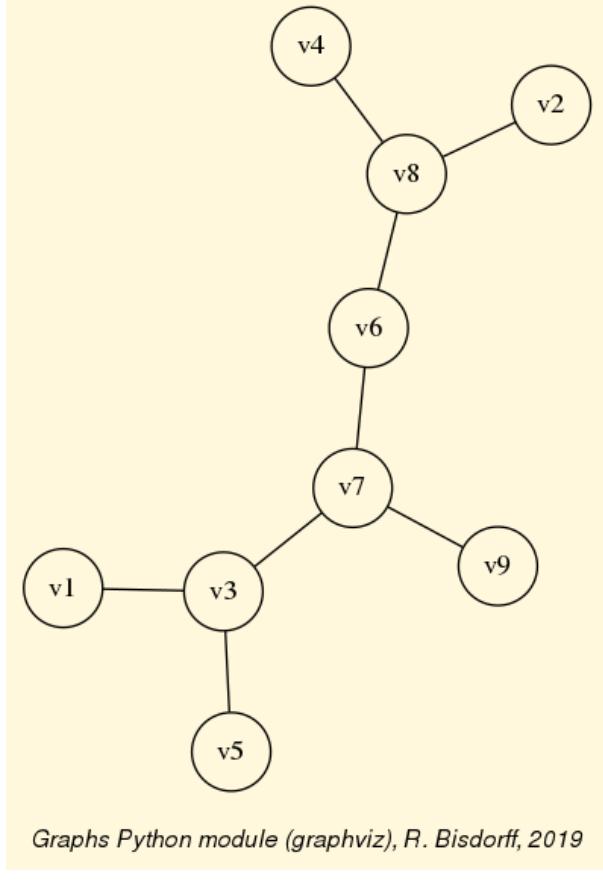


Fig. 6.19: Random Tree instance of order 9

A tree graph of order n contains $n-1$ edges (see Line 8 and 9) and we may distinguish vertices like v_1, v_2, v_4, v_5 or v_9 of degree 1, called the **leaves** of the tree, and vertices like v_3, v_6, v_7 or v_8 of degree 2 or more, called the **nodes** of the tree.

The structure of a tree of order $n > 2$ is entirely characterised by a corresponding *Prüfer code* -i.e. a *list of vertices keys*- of length $n-2$. See, for instance in Line 12 the code ['v3', 'v8', 'v8', 'v3', 'v7', 'v6', 'v7'] corresponding to our sample tree graph t .

Each position of the code indicates the parent of the remaining leaf with the smallest vertex label. Vertex v_3 is thus the parent of v_1 and we drop leaf v_1 , v_8 is now the parent of leaf v_2 and we drop v_2 , vertex v_8 is again the parent of leaf v_4 and we drop v_4 , vertex v_3 is the parent of leaf v_5 and we drop v_5 , v_7 is now the parent of leaf v_3 and we may drop v_3 , v_6 becomes the parent of leaf v_8 and we drop v_8 , v_7 becomes now the parent of leaf v_6 and we may drop v_6 . The two eventually remaining vertices, v_7 and v_9 , give the last link in the reconstructed tree (see [BAR-1991]).

It is as well possible to first, generate a random *Prüfer* code of length $n-2$ from a set of n vertices and then, construct the corresponding tree of order n by reversing the procedure illustrated above (see [BAR-1991]).

```

1  >>> verticesList = ['v1', 'v2', 'v3', 'v4', 'v5', 'v6', 'v7']
2  >>> n = len(verticesList)
3  >>> import random

```

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```

4  >>> random.seed(101)
5  >>> code = []
6  >>> for k in range(n-2):
...      code.append( random.choice(verticesList) )
8
9  >>> print(code)
10 ['v5', 'v7', 'v2', 'v5', 'v3']
11 >>> t = RandomTree(prueferCode=['v5', 'v7', 'v2', 'v5', 'v3'])
12 >>> t
13 *----- Graph instance description -----*
14 Instance class    : RandomTree
15 Instance name     : randomTree
16 Graph Order       : 7
17 Graph Size        : 6
18 Valuation domain : [-1.00; 1.00]
19 Attributes        : ['name', 'order', 'vertices', 'valuationDomain',
20                      'edges', 'prueferCode', 'size', 'gamma']
21 *---- RandomTree specific data ----*
22 Prüfer code   : ['v5', 'v7', 'v2', 'v5', 'v3']
23 >>> t.exportGraphViz('tutPruefTree')
24 *---- exporting a dot file for GraphViz tools -----*
25 Exporting to tutPruefTree.dot
26 neato -Tpng tutPruefTree.dot -o tutPruefTree.png

```

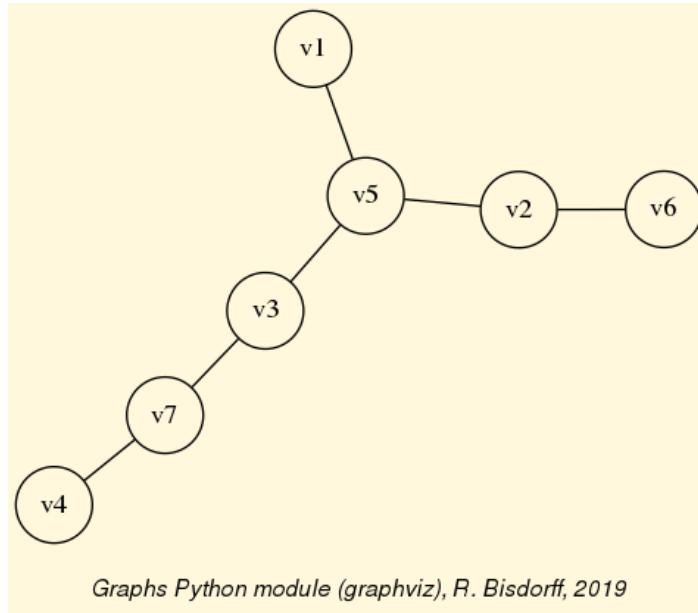


Fig. 6.20: Tree instance from a random Prüfer code

Following from the bijection between a labelled tree and its *Prüfer* code, we actually know that there exist n^{n-2} different tree graphs with the same n vertices.

Given a genuine graph, how can we recognize that it is in fact a tree instance ?

Recognizing tree graphs

Given a graph g of order n and size s , the following 5 assertions $A1$, $A2$, $A3$, $A4$ and $A5$ are all equivalent (see [BAR-1991]):

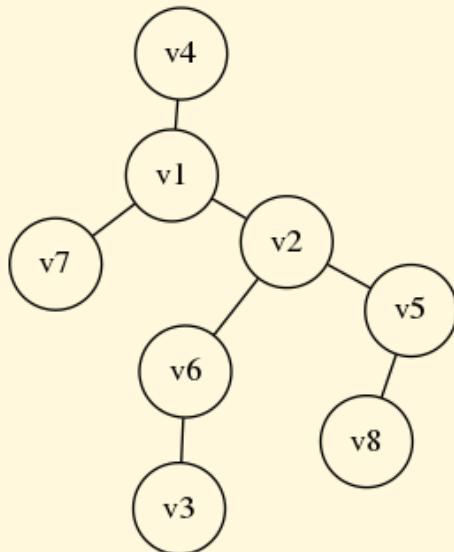
- $A1$: g is a tree;
- $A2$: g is without (chordless) cycles and $n = s + 1$;
- $A3$: g is connected and $n = s + 1$;
- $A4$: Any two vertices of g are always connected by a *unique path*;
- $A5$: g is connected and *dropping* any single edge will always disconnect g .

Assertion $A3$, for instance, gives a simple test for recognizing a tree graph. In case of a *lazy evaluation* of the test in Line 3 below, it is opportune, from a computational complexity perspective, to first, check the order and size of the graph, before checking its potential connectedness.

```
1 >>> from graphs import RandomGraph
2 >>> g = RandomGraph(order=8,edgeProbability=0.3,seed=62)
3 >>> if g.order == (g.size +1) and g.isConnected():
4 ...     print('The graph is a tree ?', True)
5 ... else:
6 ...     print('The graph is a tree ?',False)
7
8 The graph is a tree ? True
```

The random graph of order 8 and edge probability 30%, generated with seed 62, is actually a tree graph instance, as we may readily confirm from its *graphviz* drawing in Fig. 6.21 (see also the `isTree()` method for an implemented alternative test).

```
>>> g.exportGraphViz('test62')
*---- exporting a dot file for GraphViz tools -----*
Exporting to test62.dot
fdp -Tpng test62.dot -o test62.png
```



Graphs Python module (graphviz), R. Bisдорff, 2019

Fig. 6.21: Recognizing a tree instance

Yet, we still have to recover its corresponding *Prüfer* code. Therefore, we may use the `tree2Pruefer()` method.

```
>>> from graphs import TreeGraph
>>> g.__class__ = TreeGraph
>>> g.tree2Pruefer()
['v6', 'v1', 'v2', 'v1', 'v2', 'v5']
```

In Fig. 6.21 we also notice that vertex v_2 is actually situated in the **centre** of the tree with a neighborhood depth of 2. We may draw a correspondingly rooted and oriented tree graph.

```
>>> g.computeGraphCentres()
{'v2': 2}
>>> g.exportOrientedTreeGraphViz(fileName='rootedTree',
...                                     root='v2')
```

— exporting a dot file for GraphViz tools —— Exporting to
rootedTree.dot dot -Grankdir=TB -Tpng rootedTree.dot -o rootedTree.png

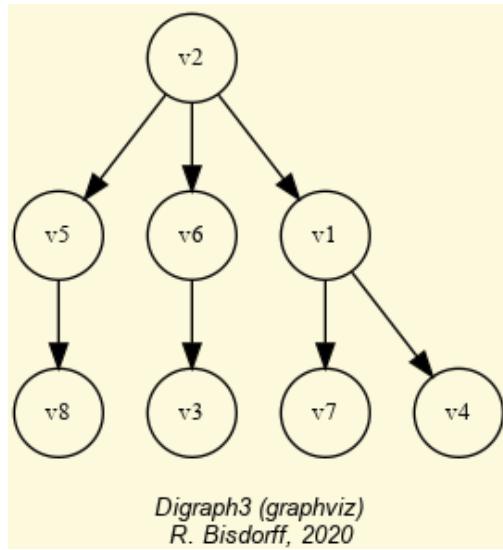


Fig. 6.22: Drawing an oriented tree rooted at its centre

Let us now turn our attention toward a major application of tree graphs, namely *spanning trees* and *forests* related to graph traversals.

Spanning trees and forests

With the `RandomSpanningTree` class we may generate, from a given **connected** graph g instance, **uniform random** instances of a **spanning tree** by using *Wilson's algorithm* [WIL-1996]

Note

Wilson's algorithm *only* works for connected graphs⁴.

```

1  >>> from graphs import RandomGraph, RandomSpanningTree
2  >>> g = RandomGraph(order=9, edgeProbability=0.4, seed=100)
3  >>> spt = RandomSpanningTree(g)
4  >>> spt
5  ----- Graph instance description -----
6  Instance class    : RandomSpanningTree
7  Instance name     : randomGraph_randomSpanningTree
8  Graph Order       : 9
9  Graph Size        : 8
10 Valuation domain : [-1.00; 1.00]
11 Attributes        : ['name', 'vertices', 'order', 'valuationDomain',
12                           'edges', 'size', 'gamma', 'dfs', 'date',
13                           'dfsx', 'prueferCode']
```

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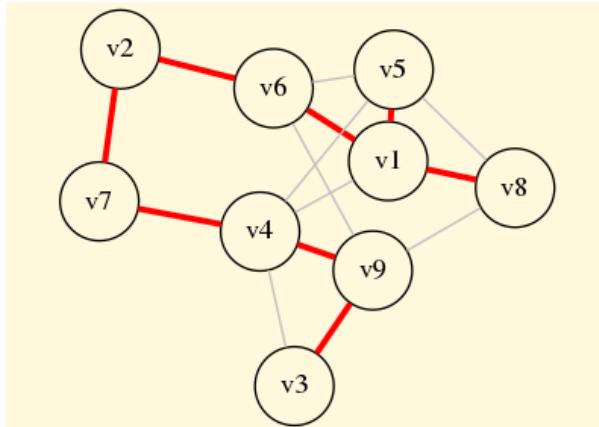
⁴ Wilson's algorithm uses *loop-erased random walks*. See https://en.wikipedia.org/wiki/Loop-erased_random_walk.

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```

14     *---- RandomTree specific data ----*
15     Prüfer code : ['v7', 'v9', 'v5', 'v1', 'v8', 'v4', 'v9']
16 >>> spt.exportGraphViz(fileName='randomSpanningTree',
17                         WithSpanningTree=True)
18     *---- exporting a dot file for GraphViz tools -----*
19     Exporting to randomSpanningTree.dot
20     [[['v1', 'v5', 'v6', 'v5', 'v1', 'v8', 'v9', 'v3', 'v9', 'v4',
21       'v7', 'v2', 'v7', 'v4', 'v9', 'v8', 'v1']]]
22     neato -Tpng randomSpanningTree.dot -o randomSpanningTree.png

```



Graphs Python module (graphviz), R. Bisdorff, 2019

Fig. 6.23: Random spanning tree

More general, and in case of a not connected graph, we may generate with the `RandomSpanningForest` class a *not necessarily uniform* random instance of a **spanning forest** -one or more random tree graphs- generated from a **random depth first search** of the graph components' traversals.

```

1 >>> g = RandomGraph(order=15,edgeProbability=0.1,seed=140)
2 >>> g.computeComponents()
3 [{ 'v12', 'v01', 'v13'}, { 'v02', 'v06'},
4   { 'v08', 'v03', 'v07'}, { 'v15', 'v11', 'v10', 'v04', 'v05'},
5   { 'v09', 'v14'}]
6 >>> fromgraphs import RandomSpanningForest
7 >>> spf = RandomSpanningForest(g,seed=100)
8 >>> spf.exportGraphViz(fileName='spanningForest',WithSpanningTree=True)
9     *---- exporting a dot file for GraphViz tools -----*
10    Exporting to spanningForest.dot
11    [[['v03', 'v07', 'v08', 'v07', 'v03'],
12      ['v13', 'v12', 'v13', 'v01', 'v13'],
13      ['v02', 'v06', 'v02'],
14      ['v15', 'v11', 'v04', 'v11', 'v15', 'v10', 'v05', 'v10', 'v15']],

```

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```
15 ['v09', 'v14', 'v09']]
16 neato -Tpng spanningForest.dot -o spanningForest.png
```

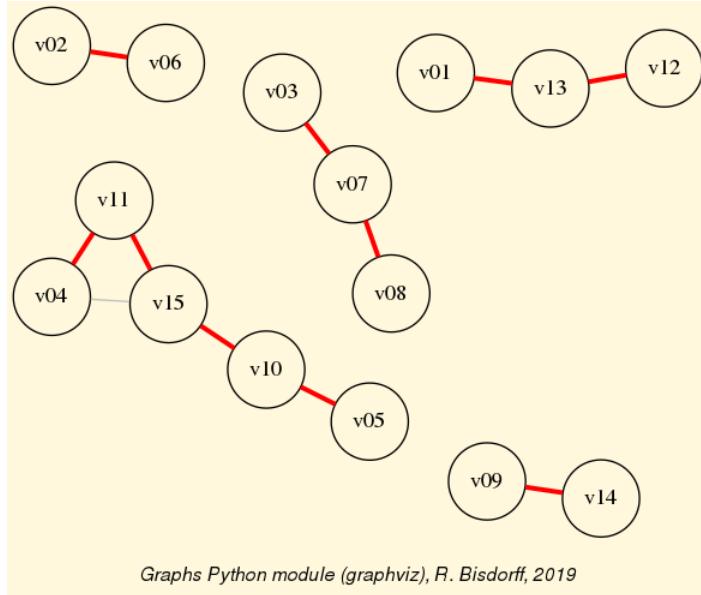


Fig. 6.24: Random spanning forest instance

Maximum determined spanning forests

In case of valued graphs supporting weighted edges, we may finally construct a **most determined** spanning tree (or forest if not connected) using *Kruskal's greedy minimum-spanning-tree algorithm*⁵ on the *dual* valuation of the graph [KRU-1956].

We consider, for instance, a randomly valued graph with five vertices and seven edges bipolar-valued in [-1.0; 1.0].

```
1 >>> from graphs import RandomValuationGraph
2 >>> g = RandomValuationGraph(seed=2)
3 >>> print(g)
4 ----- Graph instance description -----
5 Instance class      : RandomValuationGraph
6 Instance name       : randomGraph
7 Graph Order         : 5
8 Graph Size          : 7
9 Valuation domain   : [-1.00; 1.00]
10 Attributes          : ['name', 'order', 'vertices', 'valuationDomain',
11                           'edges', 'size', 'gamma']
```

To inspect the edges' actual weights, we first transform the graph into a corresponding digraph (see Line 1 below) and use the `showRelationTable()` method (see Line 2 below)

⁵ Kruskal's algorithm is a *minimum-spanning-tree* algorithm which finds an edge of the least possible weight that connects any two trees in the forest. See https://en.wikipedia.org/wiki/Kruskal%27s_algorithm.

for printing its **symmetric adjacency matrix**.

```

1 >>> dg = g.graph2Digraph()
2 >>> dg.showRelationTable()
3 * ---- Relation Table ----
4   S | 'v1'      'v2'      'v3'      'v4'      'v5'
5   -+-----+
6   'v1' |  0.00     0.91     0.90    -0.89    -0.83
7   'v2' |  0.91     0.00     0.67     0.47     0.34
8   'v3' |  0.90     0.67     0.00    -0.38     0.21
9   'v4' | -0.89     0.47    -0.38     0.00     0.21
10  'v5' | -0.83     0.34     0.21     0.21     0.00
11 Valuation domain: [-1.00;1.00]

```

To compute the most determined spanning tree or forest, we may use the `BestDeterminedSpanningForest` class constructor.

```

1 >>> from graphs import BestDeterminedSpanningForest
2 >>> mt = BestDeterminedSpanningForest(g)
3 >>> print(mt)
4 *----- Graph instance description -----
5 Instance class : BestDeterminedSpanningForest
6 Instance name  : randomGraph_randomSpanningForest
7 Graph Order    : 5
8 Graph Size    : 4
9 Valuation domain : [-1.00; 1.00]
10 Attributes     : ['name', 'vertices', 'order', 'valuationDomain',
11                      'edges', 'size', 'gamma', 'dfs',
12                      'date', 'averageTreeDetermination']
13 *---- best determined spanning tree specific data ----*
14 Depth first search path(s) :
15 [['v1', 'v2', 'v4', 'v2', 'v5', 'v2', 'v1', 'v3', 'v1']]
16 Average determination(s) : [Decimal('0.655')]

```

The given graph is connected and, hence, admits a single spanning tree (see Fig. 6.25) of **maximum mean determination** $= (0.47 + 0.91 + 0.90 + 0.34)/4 = 0.655$ (see Lines 9, 6 and 10 in the relation table above).

```

1 >>> mt.exportGraphViz(fileName='bestDeterminedspanningTree',
2 ...                           WithSpanningTree=True)
3 *---- exporting a dot file for GraphViz tools -----
4 Exporting to spanningTree.dot
5 [['v4', 'v2', 'v1', 'v3', 'v1', 'v2', 'v5', 'v2', 'v4']]
6 neato -Tpng bestDeterminedSpanningTree.dot -o
→bestDeterminedSpanningTree.png

```

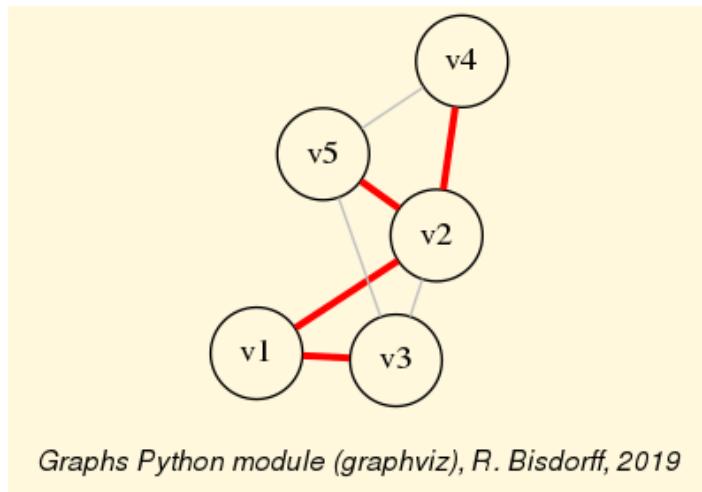


Fig. 6.25: Best determined spanning tree

One may easily verify that all other potential spanning trees, including instead the edges $\{v3, v5\}$ and/or $\{v4, v5\}$ - will show a lower average determination.

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7 Appendices

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