Paper

The problem of objective ranking: foundations, approaches and applications

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Abstract—The paper starts with the discussion of the issue of objectivity versus subjectivity, stressing that while an absolute objectivity is not attainable, nevertheless trying to be as objective as possible constitutes a higher value, necessary for hard science and technology. Dangers and errors of the subjectivist reduction of objectivity to power and money attempted by the postmodern sociology of science are discussed. Then we turn to the problem of subjective versus objective decision analysis and ranking. It is shown that while all classical decision theory aims at a rational analysis and support of subjective decisions, there are important application cases, particularly in managerial problems, when the decision maker prefers to avoid specifying her/his preferences and needs decision analysis – e.g., ranking of decision options – that is as objective as possible. An approach to decision support that might be easily adapted for such objective ranking is the reference point methodology; its application is shown on examples. One of these examples is actually not an application of the methodology, but a real life problem that motivated the development of objective ranking. The examples illustrate that objective ranking might be important for management, including also management of telecommunication networks.

Keywords— subjective ranking, objective ranking, reference point approaches, objectivity.

1. Introduction

The words *subjective* and *objective* might be used in a derogatory sense, but we shall use them in their original epistemic sense:

– subjective as resulting from personal cognition or preferences;

– objective as trying to represent outside world without bias and presuppositions.

Thus, we can say that all contemporary decision analysis, aiming at supporting the decision maker in using her/his own preferences for selecting best personal decisions, concentrates actually on computerized, rational support of subjective decisions. But what means *computerized support*? It should include at least two aspects:

– a computerized representation of knowledge (including data, rules, models) about a part of outside reality pertinent for the decision situation, which should be *as objective as possible*;

– a computerized support for combining *the subjective preferences* of an individual decision maker with an objective representation of the pertinent knowledge in selecting the actual decision.

However, there are practical cases (illustrated by examples given later) when the decision maker does not want to specify her/his individual preferences, prefers to obtain suggested decisions – or a ranking of a list of decision options specified as objectively as possible.

We know that full objectivity is impossible. This was shown already by Heisenberg [8], we discuss it in more detail later – and contemporary physics still considers a synthesis of Heisenbergian *indeterminacy* and Einsteinian *relativity* as the most important problem in science. However, technology and engineering cannot develop without trying to be as objective as possible, for example, without submitting technological tools to destructive Popperian falsification tests.

Postmodern social science ridicules Popperian falsificationism and postulates that all our knowledge is subjective, but we shall discuss the errors of postmodern sociology of science later. Here we just conclude that *there is a need of both subjective and objective aspects of knowledge and decisions*.

2. Objectivity versus subjectivity

At the beginning, we must add some philosophical comments on subjectivity and objectivity. The destruction of the industrial era episteme [25, 28] – sometimes called not quite precisely positivism or scientism – started early, e.g., since Heisenberg [8] has shown that not only a measurement depends on a theory and on instruments, but also the very fact of measurement distorts the measured variable.

This was followed by diverse philosophical debates, summarized, e.g., by Quine [20] who has shown that the logical empiricism (neo-positivism) is logically inconsistent itself, that all human knowledge "*is a man-made fabric that impinges on existence only along the edges*". This means that there is no absolute objectivity.

However, this was quite differently interpreted by hard sciences and by technology, which nevertheless tried to remain as objective as possible, and by social sciences which, in some cases, went much further to maintain that all knowledge is subjective – results from a discourse, is constructed, negotiated, relativist, depends on power and money (see, e.g., [13]).

This has led to a general divergence of *the episteme* – the way of constructing and justifying knowledge, characteristic for a given cultural era (see [4]), we add only that also characteristic for a cultural sphere – of the following three different cultural spheres (see [25]):

– of hard and natural sciences;

– of technology proper (understood as the art of constructing tools);

– of social sciences and humanities.

Even if we (the technologists) respect the different culture of social sciences and humanities, we must protest against extreme epistemic interpretations that become fashionable today. For example, some our colleagues maintain that "*There is no universe, but only a multiverse – and to realize this is liberating*". We propose that they liberate themselves by falsifying their conviction, applying a hard wall test: posit yourself against hard wall, close your eyes, and try to convince yourself that, since there is only a multiverse (and, according to the quantum theory, there is a nonzero probability of penetrating the wall), the wall does not exist. If you cannot convince yourself, then there is no multiverse, because reality apparently has some universal features; if you can convince yourself, run with your head ahead, in order to falsify your conviction.

On the other hand, even if we should try to develop an integrated episteme for the new era of knowledge civilization (see [28]), this new episteme must take into account that absolute objectivity is not attainable, because of the following basic principles.

Multimedia principle: words are just an approximate code to describe much more complex reality, visual and generally preverbal information is much more powerful and relates to intuitive knowledge and reasoning; future records of the intellectual heritage of humanity will have multimedia character, thus stimulating creativity.

This multimedia principle has many implications, but we stress here only the most obvious: if words are just an approximate code, then absolute truth and absolute objectivity are obviously not possible. But we need truth even in elementary social discourse, need objectivity at least in technology. Thus, truth and objectivity are higher values, ideals that we try to attain as closely as possible even if they are not fully attainable.

This is related to another basic principle. The concepts of punctuated evolution from biology, order emerging out of chaos from computational modeling, emergence of software out of hardware, multiple layers of protocols in telecommunications jointly justify the following.

Emergence principle: new concepts and properties of a system emerge with increased level of complexity, and these properties are qualitatively different than and irreducible to the properties of parts of the system.

This principle implies a fundamental conceptual change. Firstly, it shows that the arguments of creationism against evolution – that evolution could not produce irreducible complexity – are ignorant of the obvious fact that the evolution of civilization, much faster than the biological evolution thus easier to observe, has recently produced several examples of the emergence of irreducible complexity, starting with the emergence of software out of hardware. Secondly, even if it might seem that emergence principle logically results from the principle of synergy or holism – that the whole is more than the sum of its parts (see [1, 2]), this is not necessarily a correct interpretation. The principle of synergy or holism does not say that the whole should have essentially different, irreducible properties, than the parts of the system.

However, we can see that higher values, such as truth or objectivity, are also higher level concepts that emerged evolutionary in civilisation evolution. Thus, they are irreducible to lower level concepts, such as power and money.

This is not just a philosophic debate. If scientific objectivity could be reduced to money and power, than managers would try to force us, engineers, to use fraudulent engineering for profit; and, more generally, postmodern sociology of science gives a nice excuse for an unlimited privatization of knowledge.

The argument for privatization of public resources is based on the phenomenon of tragedy of commons (devastation of a degradable resource, if used without limits). However, knowledge is not degradable (see [14]), it increases with use, hence it is more advantageous for a community to keep knowledge public. But there are strong economic forces today interested in an unrestricted privatization of knowledge; and postmodernism provides them with an ideology.

Thus, we should clearly point out the errors of postmodern sociology of science. For example, Latour [13] argues that since the concepts of nature and reality are constructed by us, they cannot be the cause of our knowledge, because an effect cannot be a cause. His argument is logically erroneous, in obvious ignorance about the mechanism of positive feedback that is the basis of the evolution of knowledge. Hence, it is not true that knowledge can be reduced to money and power.

In order to show that the postmodern episteme is not the only possible one, we present here another description of the relation of human knowledge to nature [28]. First, from a technological perspective we do not accept the assumption of postmodern philosophy that "nature" is only a construction of our minds and has only local character. Of course, the word nature refers both to the construction of our minds and to something more – to some persisting, universal (to some degree) aspects of the world surrounding us. People are not alone in the world; in addition to other people, there exists another part of reality, that of nature, although part of this reality has been converted by people to form human-made, mostly technological systems. There are aspects of reality that are local and multiple, there are aspects that are more or less universal.

Second, the general relation of human knowledge to reality might be described as follows. People, motivated by curiosity and aided by intuition and emotions, observe reality and formulate hypotheses about properties of nature, of other people, of human relations; they also construct tools; together, we call all this knowledge. People test and evaluate the knowledge constructed by them by applying it to reality: perform destructive tests of tools, devise critical empirical tests of theories concerning nature, apply and evaluate theories concerning social and economic relations; in general, we can consider this as a generalized principle of falsification, broader than defined by Karl Popper even in his later works [19].

Such a process can be represented as a general spiral of evolutionary knowledge creation, see Fig. 1. We observe reality (either in nature or in society) and its changes, compare our observations with human heritage in knowledge (the transition *Observation*). Then our intuitive and emotive knowledge helps us to generate new hypotheses (*Enlightenment*) or to create new tools; we apply them to existing reality (*Application*), usually with the goal of achieving some changes, modifications of reality (*Modification*); we observe them again.

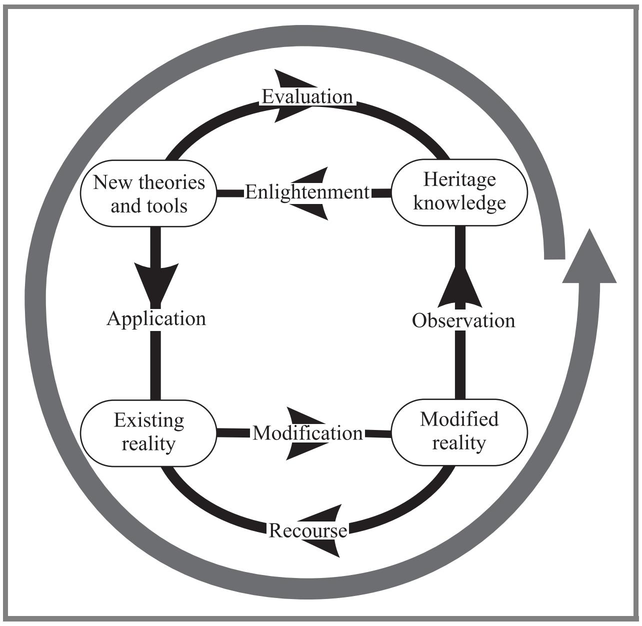

Fig. 1. The general OEAM spiral of evolutionary knowledge creation.

It is important, however, to note that many other transitions enhance this spiral. First is the natural evolution in time: modified reality becomes existing reality through *Recourse*. Second is the evolutionary selection of tested knowledge: most new knowledge might be somehow recorded, but only the positively tested knowledge, resilient to falsification attempts, remains an important part of human heritage (*Evaluation*); this can be interpreted as an objectifying, stabilizing feedback. Naturally, there might be also other transitions between the nodes indicated in the spiral model, but the transitions indicated in Fig. 1 are the most essential ones.

Thus, nature is not only the effect of construction of knowledge by people, nor is it only the cause of knowledge: it is both cause and effect in a positive feedback loop, where more knowledge results in more modifications of nature and more modifications result in more knowledge. As it is typical for positive feedback loops, the overall result is an avalanche-like growth; and this avalanche-like growth, if unchecked by stabilizing negative feedbacks, beside tremendous opportunities creates also diverse dangers, usually not immediately perceived but lurking in the future. Thus, the importance of selecting knowledge that is as objective as possible relates also to the fact that avalanche-like growth creates diverse threats: we must leave to our children best possible knowledge in order to prepare them for dealing with unknown future.

This description of a spiral-like, evolutionary character of knowledge creation is consistent with our technological cognitive horizon, and slightly different than presented in [9] from a position of an economic cognitive horizon. It is an extension of the concept of objective knowledge promoted by Popper [19], but admits relativistic interpretations; it only postulates objectivity as a higher level value, similar to justice: both absolute justice and absolute objectivity might be not attainable, but are important, worth striving for, particularly if we take into account uncertainty about future (see also [21]).

After outlining this philosophic background, we can turn now to the problem of objective versus subjective ranking of decision options. We start, however, with an outline of reference point approaches to the problem of ranking.

3. Reference point approaches: the discrete case

We assume here that the admissible decisions are given by just a list of considered decision options $\boldsymbol{x}_k \in X_0$, where X_0 denotes the set of these options. We assume that we have a decision problem with J criteria, indexed by $j = 1, \ldots, J$ (also denoted by $j \in \boldsymbol{J}$), and K decision options called also alternatives, indexed by $k = 1, \ldots, K$ or $k = \mathrm{A}, \mathrm{B}, \ldots, \mathrm{H}$ (also denoted by $k \in \boldsymbol{K} = \{1, \ldots, K\}$). The corresponding criteria values are denoted by q_{jk}; we assume that all are maximized or converted to maximized variables. The maximal values $\max_{k \in \boldsymbol{K}} q_{jk} = q_j^{up}$ are called upper bounds for criteria and are often equivalent to the components of so called ideal or utopia point $\boldsymbol{q}^{uto} = \boldsymbol{q}^{up} = (q_1^{up}, \ldots, q_j^{up}, \ldots, q_J^{up})$ – except for cases when they were established a priori as a measurement scale. The minimal values $\min_{k \in \boldsymbol{K}} q_{jk} = q_j^{lo}$ are called lower bounds and, generally, are not equivalent to the components of so called nadir point $\boldsymbol{q}^{nad} \geq \boldsymbol{q}^{lo} = (q_1^{lo}, \ldots, q_j^{lo}, \ldots, q_J^{lo})$; the nadir point $\boldsymbol{q}^{nad}$ is defined similarly as the lower bound point $\boldsymbol{q}^{lo}$, but with minimization restricted to Pareto optimal or efficient or nondominated alternatives (see, e.g., [3]). An alternative $k^* \in K$ is Pareto optimal (Pareto-nondominated or shortly nondominated, also called efficient), if there is no other alternative $k \in \boldsymbol{K}$ that dominates k^*, that is, if we denote $\boldsymbol{q}_k = (q_{1k}, \ldots, q_{jk}, \ldots, q_{Jk})$, there is no $k \in \boldsymbol{K}$ such that $\boldsymbol{q}_k \geq \boldsymbol{q}_{k^*}$, $\boldsymbol{q}_k \neq \boldsymbol{q}_{k^*}$.

While the reference point approach is typically described for the continuous case (with a nonempty interior of X_0, thus an infinite number of options in this set), we shall concentrate here on the discrete case, with a finite number of decision options K, for which case the reference point approach is equally or even particularly suitable. This is because when we consider the outcome set Q_0, that is, the set of criteria vectors $\boldsymbol{q}_k$ corresponding to decision options $\boldsymbol{x}_k$, is in this case obviously not convex, and important elements of Pareto outcome set might be contained in the interior, not on the boundary of the convex cover of this set. Thus, with any other method – particularly with a weighted sum, but also with many nonlinear utility approximations – we run the risk of missing important Pareto points in the discrete case. We do not have this risk when using reference point approaches, because of their full controllability property, not possessed by utility functions nor by weighted sums, see later comments.

The most general specification of preferences of a decision maker contains a selection of decision outcomes chosen as criteria, accompanied by defining a partial order in the space of criteria – simply asking the decision maker which criteria should be maximized and which minimized (or stabilized). Here we consider only the simplest case when all criteria are maximized.

When analyzing a decision problem in the discrete case, we might be interested in:

- finding the best solution (option),
- finding all Pareto-optimal solutions (options),
- ranking all options,
- classifying all options.

Here we shall consider mostly the problem of ranking. There are several versions of methods belonging to the general class of reference point approaches (see [15, 26]). Here we describe a method based on a specification of double reference levels – aspiration level a_j and reservation level r_j – for each criterion. After this specification, the approach uses a nonlinear aggregation of criteria by an achievement function that is performed in two steps.

We first count achievements for each individual criterion or satisfaction with its values by transforming it (monotonically and piece-wise linearly), e.g., in the case of maximized criteria as shown in Eq. (1) below. In a discrete decision problem we can choose these coefficients to have a reasonable interpretation of the values of the partial (or individual) achievement function. Since the range of [0; 10] points is often used for eliciting expert opinions about subjectively evaluated criteria or achievements, we adopted this range in Eq. (1) below for the values of a partial achievement function $\sigma_j(q_j, a_j, r_j)$:

$$\sigma_j(q_j,a_j,r_j) = \begin{cases} \dfrac{\alpha(q_j - q_j^{lo})}{(r_j - q_j^{lo})} & \text{for } q_j^{lo} \leq q_j < r_j, \\ \dfrac{\alpha + (\beta - \alpha)(q_j - r_j)}{(a_j - r_j)} & \text{for } r_j \leq q_j < a_j, \\ \dfrac{\beta + (10 - \beta)(q_j - a_j)}{(q_j^{up} - a_j)} & \text{for } a_j \leq q_j \leq q_j^{up}. \end{cases} \tag{1}$$

The parameters α and β, $0 < \alpha < \beta < 10$, in this case denote correspondingly the values of the partial achievement function for $q_j = r_j$ and $q_j = a_j$. The value $\sigma_{jk} = \sigma_j(q_{jk}, a_j, r_j)$ of this achievement function for a given alternative $k \in \boldsymbol{K}$ signifies the satisfaction level with the criterion value for this alternative. Thus, the above transformation assigns satisfaction levels from 0 to α (say, $\alpha = 3$) for criterion values between q_j^{lo} and r_j, from α to β (say, $\beta = 7$) for criterion values between r_j and a_j, from β to 10 for criterion values between a_j and q_j^{up}.

After this transformation of all criteria values, we might use then the following form of the overall achievement function:

$$\sigma(\boldsymbol{q},\boldsymbol{a},\boldsymbol{r}) = \min_{j \in \boldsymbol{J}} j_i(q_j,a_i,r_j) + \varepsilon/J \sum_{j \in \boldsymbol{J}} \sigma_j(q_j,a_j,r_j), \tag{2}$$

where $\boldsymbol{q} = (q_1, \ldots q_j, \ldots q_J)$ is the vector of criteria values, $\boldsymbol{a} = (a_1, \ldots a_j, \ldots a_J)$ and $\boldsymbol{r} = (r_1, \ldots r_j, \ldots r_J)$ are the vectors of aspiration and reservation levels, while $\varepsilon > 0$ is a small regularizing coefficient. The achievement values $\sigma_k = \sigma(\boldsymbol{q}_k, \boldsymbol{a}, \boldsymbol{r})$ for all $k \in \boldsymbol{K}$ can be used either to select the best alternative, or to order the options in an overall ranking list or classification list, starting with the highest achievement value.

The properties of such functions are, also for the discrete case:

- partial order approximation: the level sets of such functions approximate closely the positive cone defining the partial order (see [24]);
- full controllability: given any point $\boldsymbol{q^*}$ in criteria space that is (properly, with a priori bounded trade-off coefficients[1]) Pareto-nondominated and corresponds to some decision option, we can always

[1]By a properly Pareto-nondominated option with a priori bounded trade-off coefficients, called also an ε-properly Pareto-nondominated alternative, we understand a Pareto-nondominated alterbnative with trade-off coefficients bounded by a given large number, e.g., the number $1 + 1/\varepsilon$ [26]. The property that any ε-properly Pareto-nondominated alternative can be selected as the best by maximizing an achievement function is called the controllability property and is much stronger than the efficiency property (that any maximum of a function, which is strictly monotone with respect to the partial order, is Pareto-nondominated). The controllability property is possessed by functions such as (2) that are not only strictly monotone with respect to the partial order, but also have level sets approximating the positive cone that defines the partial order. This property does not depend on convexity assumptions [24].

choose such reference levels – in fact, it suffices to set aspiration levels equal to the components of $\boldsymbol{q}^*$ – that the maximum of the achievement function (2) is attained precisely at this point;

– dependence of implied weighting coefficients on the currently specified reference points (see [26]);

– possibility of using $\varepsilon = 0$ with nucleolar minimax approach [12, 16]: consider first the minimal, worst individual criterion achievement σ_j computed as above with $\varepsilon = 0$; if two options k_1 and k_2 (or more of them) have the same achievement value, we order them according to the second worst individual criterion achievement, and so on.

4. The issue of objective ranking

The ranking of discrete options is a classical problem of multi-attribute decision analysis; however, all classical approaches – whether of Keeney and Raiffa [11], or of Saaty [22], or of Keeney [10] – concentrate on *subjective ranking*. By this we do not mean intuitive subjective ranking, which can be done by any experienced decision maker based on her/his intuition, but rational subjective ranking, based on the data relevant for the decision situation – however, using an approximation of personal preferences in aggregating multiple criteria.

And therein is the catch: in many practical situations, if the decision maker wants to have a computerized decision support and rational ranking, she/he does not want to use personal preferences, prefers to have some objective ranking. This is often because the decision is not only a personal one, but affects many people – and it is usually very difficult to achieve an intersubjective rational ranking, accounting for personal preferences of all people involved. This obvious fact is best illustrated by the following example.

Suppose an international corporation consists of six divisions A–F. Suppose these units are characterized by diverse data items, such as name, location, number of employees, etc. However, suppose that the Chief Executive Officer (CEO) of this corporation is really interested in ranking or classification of these divisions taking into account the following attributes used as criteria: 1) profit (in % of revenue), 2) market share (m.share, in % of supplying a specific market sector), 3) internal collaboration (i.trade, in % of revenue coming from supplying other divisions of the corporation), and 4) local social image (l.s.i., meaning public relations in the society where it is located, evaluated on a scale 0–100 points). All these criteria are maximized, improve when increased. An example of data of this type is shown in Table 1 (with data distorted for privacy reasons).

Suppose the CEO of this corporation hires a consulting company and asks for an objective ranking of these six divisions. The approach that can be easily adapted for rational objective ranking is reference point approach – because reference levels needed in this approach can be either defined subjectively by the decision maker, or established objectively statistically from the given data set. We can use this approach not only for objective ranking, but also for objective classification, using methods as indicated above with objectively defined reference points.

In the next section, we shall show below how to apply this approach for the simple example given in Table 1. We denoted by q_{jk} the value of a criterion q_j for the decision option $k \in \boldsymbol{K}$, and the achievement values $\sigma_k = \sigma(\boldsymbol{q}_k, \boldsymbol{a}, \boldsymbol{r})$ for all $k \in \boldsymbol{K}$ can be used to order the options in an overall ranking list, starting with the highest achievement value. Now, the question is: how to define aspiration levels $\boldsymbol{a}$ and reservation levels $\boldsymbol{r}$ in order to obtain rational objective ranking? Several ways were listed in [5]: neutral, statistical, voting; we shall concentrate here on statistical determination.

A statistical determination of reference levels concerns values m_j that would be used as basic reference levels, an upward modification of these values to obtain aspiration levels a_j, and a downward modification of these values to obtain reservation levels r_j; these might be defined as follows:

$$m_j = \sum_{k\in\boldsymbol{K}} \boldsymbol{q}_{jk}/K;\ r_j = 0.5(q_j^{lo} + m_j);\ a_j = 0.5(q_j^{up} + m_j),\ \forall j \in \boldsymbol{J}, \tag{3}$$

where K denotes the number of alternative options, thus m_j are just average values of criteria in the set of all alternative options; aspiration and reservation levels – just averages of these averages and the lower and upper bounds, respectively.

However, there are no essential reasons why we should limit the averaging to the set of alternative options ranked; we could use as well a larger set of data in order to define more adequate (say, historically meaningful) averages, or a smaller set – e.g., only the Pareto optimal options – in order to define more demanding averages and aspirations. For very large data sets, we can use, e.g., evolutionary (EMO) algorithms for an approximation of the Pareto set.

Variants of objective ranking. For the data from Table 1, we can thus present two variants of objective ranking:

– *A*: based on averages of data from this table,

– *B*: based on averages from Pareto optimal options.

See next Tables 2 and 3. Note that the more demanding ranking *B* displays a rank reversal: the divisions C and E, occupying positions 2 and 3 in ranking *A*, exchange their places in ranking *B*. This is, however, a natural phenomenon: average aspirations favour standard though good solutions, truly interesting solutions result from demanding aspirations (however, this rank reversal might disappear, if we use different values of the parameter ε).

Note also that the rank reversal also disappears if, instead of ranking, we classify the divisions into three classes:

– I: very good,

– II: good,

– III: wanting.

Table 1
Data for an example on international business management (* denotes Pareto options)

Division	Name	Location	Employees	Profit – q_1 [%]	M.share – q_2 [%]	I.trade – q_3 [%]	L.s.i. – q_4
A	Alpha	USA	250	11	8	10	40
B*	Beta	Brasilia	750	23	40	34	60
C*	Gamma	China	450	16	50	45	70
D*	Delta	Dubai	150	35	20	20	44
E*	Epsilon	C. Europe	350	18	30	20	80
F	Fi	France	220	12	8	9	30

Table 2
Example of objective ranking for data from Table 1, based on averages of all options

Ranking *A* Division	σ_1	σ_2	σ_3	σ_4	σ	Rank	Class
A	0.00	0.00	0.37	2.50	0.29	5	III
B	5.63	7.50	7.00	5.88	8.23	1	I
C	3.30	10.0	10.0	7.62	6.39	2	II
D	10.0	3.57	3.89	3.32	5.40	4	II
E	3.97	5.48	3.89	10.0	6.30	3	II
F	0.73	0.00	0.00	0.00	0.07	6	III

Table 3
Example of objective ranking for data from Table 1, based on averages of Pareto-nondominated options

Ranking *B* Division	σ_1	σ_2	σ_3	σ_4	σ	Rank	Class
A	0.00	0.00	0.29	1.80	0.21	5	III
B	5.00	6.61	6.24	5.13	7.30	1	I
C	2.50	10.0	10.0	6.73	5.28	3	II
D	10.0	3.47	3.13	2.51	4.42	4	II
E	3.33	5.04	3.13	10.0	5.43	3	II
F	0.50	0.00	0.00	0.00	0.05	6	III

Both divisions C and E remain in the class II, both for the average and for the more demanding aspirations.

In some management applications, the worst ranked options are the most interesting, because they indicate the need of a corrective action. Objective ranking was originally motivated by an actual application when evaluating scientific creativity conditions in a Japanese research university, Japan Advanced Institute of Science and Technology (JAIST), (see [23]). Actually, it is misleading to call it an application; a real life problem was first solved innovatively, which motivated later the development of theory. This often happens in technology development: technology is not necessarily and not only an application of basic natural science, it often precedes theoretical developments – such as invention of a wheel preceded the concept of a circle, a telescope preceded optics.

The evaluation was based on survey results. The survey included 48 questions with diverse answers and over 140 respondents with diverse characteristics: school affiliation (JAIST consists of three schools), nationality (Japanese or foreign – the latter constitute over 10% of young researchers at JAIST), research position (master students, doctoral students, research associates, etc.). In total, the data base was not very large, but large enough to create computational problems.

The questions were of three types:

- assessment questions, assessing the situation between students and at the university; the most critical questions of this type might be selected as those that correspond to worst responses;
- importance questions, assessing importance of a given subject; the most important questions might be considered as those that correspond to best responses;
- controlling questions, testing the answers to the first two types by indirect questioning revealing responder attitudes or asking for a detailed explanation.

For the first two type of questions, responders were required to tick appropriate responses in the scale $\boldsymbol{vg}$ (very good), $\boldsymbol{g}$ (good), $\boldsymbol{a}$ (average), $\boldsymbol{b}$ (bad), $\boldsymbol{vb}$ (very bad) – sometimes in an inverted scale if the questions were negatively formulated. Answers to all questions of first two types were evaluated on a common scale, as a percentage distribution (histogram) of answers $\boldsymbol{vg}-\boldsymbol{g}-\boldsymbol{a}-\boldsymbol{b}-\boldsymbol{vb}$. The interpretation of the evaluation average was almost bad; if we want most answers to be very good and good, we admit not many to be average.

Therefore, in this case $\boldsymbol{J}=\boldsymbol{G}\cup\boldsymbol{B}$, $\boldsymbol{G}=\{\boldsymbol{vg},\boldsymbol{g}\}$, $\boldsymbol{B}=\{\boldsymbol{a},\boldsymbol{b},\boldsymbol{vb}\}$; the statistical distributions (percentage histograms) of answers were interpreted in the sense of multiple criteria optimization, with $j\in\boldsymbol{G}=\{\boldsymbol{vg},\boldsymbol{g}\}$ as quality indicators that should be maximized, and $j\in\boldsymbol{B}=\{\boldsymbol{a},\boldsymbol{b},\boldsymbol{vb}\}$ as quality indicators to be minimized.

A reference point approach was proposed for this particular case of ranking probability distributions; other approaches are usually more complicated (see, e.g., [17]). However, when the dean of the School of Knowledge Science in JAIST (Yoshiteru Nakamori) was asked to define his preferences or preferred aspiration levels, the reality of the managerial situation overcome his theoretical background: he responded "*in this case, I want the ranking to be as objective as possible – I must discuss the results with the deans of other schools and with all professors*". This was the origin of reflection on objective versus subjective rational ranking.

Thus, a statistical average of the percentages of answers in the entire data set was taken as the reference distribution or profile. Since such a reference profile might result in good but standard answers, some artificial reference distributions were also constructed as more demanding than the average one; averages over Pareto optimal options were not computed because of the complexity of the data set.

The detailed results of the survey were also very useful for university management (see [23]). It was found that seven questions of the first (assessment) type ranked as worst practically did not depend on the variants of ranking; thus, the objective ranking gave robust results as to the problems that required most urgent intervention by the university management. The best ranked questions of the second (importance) type were more changeable, only three of them consistently were ranked among the best ones in diverse ranking profiles. Moreover, a rank reversal phenomenon was observed: if the average reference distribution was used, best ranked were questions of rather obvious type, more interesting results were obtained when using more demanding reference profile.

Another possible application of the concept of objective ranking is the issue of detecting a significant event in a network (say, a failure of a link in a computer network). We can observe certain characteristic variables in the network and their histograms – empirical probability distributions. In the case of failure, these probability distributions will change as compared to the case of normal network functions; the issue is to use such change to identify the type of the event. Thus, the decision options $k\in\boldsymbol{K}$ in this problem are possible types of events; for each type of event, we might have a reference probability distribution, obtained, e.g., via network simulation. In such a case, the detection of the type of event is equivalent to checking which reference probability distribution is the closest to the actual empirical distribution; this can be done using also reference profile approach with stabilized criteria. However, another approach is to try to define a partial order in the space of histograms that would represent the given problem of event detection, and use an objective ranking approach to produce a ranking list of types of events, given an empirical histogram. This will be the subject of further studies (see [6]).

5. Conclusions

We discussed in this paper some aspects of the general issue of objectivity versus subjectivity, with the conclusion that objectivity is a higher value, similar to justice: it might be not fully attainable, but it is worth striving for. We have also shown that the reduction of objectivity to power and money, suggested by postmodern sociology of science, is not only based on superficial reductionism, but also contains logical errors.

We presented in this paper the issue of objective ranking defined as dependent only on a given set of data, relevant for the decision situation, and independent of any more detailed specification of personal preferences than that given by defining criteria and the partial order in criterion space. Rational objective ranking can be based on reference point approach, because reference levels needed in this approach can be established objectively statistically from the given data set.

Examples show that such objective ranking can be very useful in many management situations.

There are several possible topics for further study, such as the relation of objective ranking obtained by reference point approaches and objective ranking obtained by rough set approaches, since the latter also can be seen as dependent only on a given set of data, on an informational system in the sense of Zdzisław Pawlak (see [18] and [7]), or the issue of using multiobjective comparison of empirical statistical profiles for event detection in telecommunication networks [6].

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