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The Academic Journal Ranking Problem: A Fuzzy-Clustering Approach

Stefano Benati

Università di Trento, Italy

Silvana Stefani

Università di Milano Bicocca, Italy

Abstract: The Academic Journal Ranking Problem consists in formulating a formal assessment of scientific journals. An outcome variable must be constructed that allows valid journal comparison, either as a set of tiers (ordered classes) or as a numerical index. But part of the problem is also to devise a procedure to get this outcome, that is, how to get and use relevant data coming from expert opinions or from citations database. We propose a novel approach to the problem that applies fuzzy cluster analysis to peer reviews and opinion surveys. The procedure is composed of two steps: the first is to collect the most relevant qualitative assessments from international organizations (for example, the ones available in the Harzing database) and, as *inductive* analysis, to apply fuzzy clustering to determine homogeneous journal classes; the second *deductive* step is to determine the hidden logical rules that underlies the classification, using a classification tree to reproduce the same patterns of the first step.

Our approach is applied to the classification of 138 academic journals that were selected by members of AMASES, an Italian mathematics association, as the most prominent journals of our field. The clusters that are determined by our method show that rankings are affected by two hidden dimensions: one is the academic prestige of a publication, but the other is the disciplinary diffusion of a mathematics subfield. In particular, mathematics journals that are close to finance or economics are usually ranked better than journals dealing with linear algebra or systems dynamics.

Keywords: Fuzzy clustering model; Classification tree; Journal quality problem; Harzing data base; Impact Factor.

MSC classification: 90B50 - Management decision making, 90B90 Case-oriented studies

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Authors' Addresses: Stefano Benati, Dipartimento di Sociologia e Ricerca sociale, Università di Trento, Via Verdi 5, 38100 Trento, Italy, e-mail: stefano.benati@unitn.it; Silvana Stefani, Dipartimento di Metodi Quantitativi per le Scienze Economiche ed Aziendali, Università di Milano Bicocca, Piazza dell'Ateneo Nuovo 1, 20126 Milano, Italy, e-mail: silvana.stefani@unimib.it.

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1. Introduction

One of the basic problems of the scientific community nowadays is to assess the quality of academic journals. It is an important problem for library management, of course, since the most relevant journals should be subscribed by the University libraries. But, most prominently, the productivity of a scientific project, a department, or individual researcher is assessed by the quality of published papers. Undoubtedly, it has strong consequences on funding decisions, career advancements and so on, and many organizations proposed their rankings (Kalaitzidakis, Mamuneas, and Stengostzidakis 2003; Lubrano, Bauwens, Kirman, and Protopopescu 2003; Mingers and Harzing 2006). The importance of the problem justifies the stream of multi-disciplinary research that is committed to develop new methodologies for journal rankings. To survey early experiences on the subject, included annotated bibliography, see Donohue and Fox (2000); Zhou, Ma and Turban (2001).

In this paper, we report the experience of the AMASES, an Italian association of Mathematics professors[1]. In 2004, the Association appointed a Scientific committee to set up a list of academic journals that should represent the main AMASES scientific interests. This list should represent a guide for submitting papers to young researchers, but it will be also useful to determine the quality of research projects, individual careers, and so on. After collecting peer opinions, the Committee could compile a preliminary list composed of 138 academic journals, on which there was general agreement on being the most representative for our job.

After compilation, the list posed two questions to the Committee. There were prestigious and influential journals, but also sectorial or regional bulletins. So, how to establish quality tiers, such that most important journals were distinguished from the less relevant? Moreover, it was soon clear that the list was composed of both mathematics and economics journals. This can be easily explained: some economics journals require a good mathematics sophistication, e.g. "Econometrica", and the association consists of Mathematics professors in Economics faculties: clearly, it affected their assessments. Therefore there was a second question, how quality tiers could reflect the different composition of the list? Answering those questions is what will be called the Journal Ranking Problem.

In the literature, the Journal Ranking Problem has been addressed using two main approaches. One is to use citation indexes, the second is to use opinion surveys. The first method tries to establish a statistical index to

1. AMASES is an acronym for Associazione della Matematica Applicata alle Scienze Economiche e Sociali. Its members are mainly University Professors in the Faculties of Economics and the association encompasses more than 400 members. Both the authors of this paper are AMASES members and prof Silvana Stefani was also member of the Scientific committee

measure the importance of a journal (Kalaitzidakis, Mamuneas, and Stengos 2003; Laband and Piette 1994). Often this index is calculated using citations, and two examples of this approach are the ISI Impact Factor (IF, Thomson Scientific 2008) and the SCImago index (SCImago 2008). The advantage of statistical indexes is that they should be objective and indisputable methods. In Thomson's words (Thomson Scientific 2008): *"[...] Journal Citation Reports present quantifiable statistical data that provides a systematic, objective way to evaluate the world's leading journals and their impact and influence in the global research community."*. But the main disadvantage of an index is that it lacks qualitative statements about journals, data that can be obtained only if assessments are supervised by experts (Cameron 2005; Figá Talamanca 2000; Gonzales and Campanario 2007; Reedijk 1998). However, if expert supervision is allowed, then there is the possibility of strategic assessments and the objectivity of an index is lost.

The second journal ranking method relies on expert knowledge or peer review, in which the assesment process is scheduled and organized. Usually a peer committee is appointed and charged to rank journals, following the judgments of its members. An example of this approach is the Delphi method (Adler and Ziglio 1996). In the first step, each expert assesses his opinion independently from each other. Then experts can revise their opinion in the second step, when all assessments are common knowledge and a general consensus must be reached. The drawback of expert opinions is that they are time consuming, and also that experts tend to be less accurate as time passes. Moreover, those methods are prone to be manipulated by individual interests. Experts know how rankings are used and then they behave strategically, as is reported in the experience of the Dutch Society of Universities (Lubrano, Bauwens, Kirman, and Protopopescu 2003).

Some authors tried to combine qualitative and quantitative assesments. For example a linear programming model can be used to combine expert opinions in a general ranking (Tse 2001). The outcome is a numerical assesment of the journal quality. In Zhou, Ma, and Turban (2001), expert opinions are combined using a fuzzy set approach, but the starting point is that each individual makes his own assessment, e.g. strategic voting cannot be avoided. One way to avoid strategic ranking by members of an association is to use and analyze peer reviews assessments that are compiled by external committees or associations. For example, an Italian association could use the French assessments for Italian purposes. Extending this approach, one committee could rely on surveys that are contained in the Harzing data base (Harzing 2005), a data base that collect academic rankings from many associations. The data set is publicly available through the Internet and it has been already used to obtain a classification of Economics journal into ordinal tiers (Mingers and Harzing 2006).

Returning to the AMASES problem, one member of the Scientific committee decided to develop an original approach to establish journal qualities. First, only quality assessments that were made by other external organizations were to be analyzed, e.g. to avoid the problem of strategic behavior, AMASES members opinions are not considered. Then tiers should be created as follows: first apply cluster analysis to obtain homogeneous groups of journals, then determine the unknown and hidden rules that are implied in that classification. More precisely, in the first step, fuzzy qualitative cluster analysis has been applied (Bezdek, Keller, Krisnapuram, and Pal 2005; Hoppner, Kruse, Klawonn, and Runkler 1999). As will be discussed later, qualitative analysis had to be used for the large amount of missing data, and fuzzy inclusion numbers and fuzzy clustering were necessary to detect journals with the same distance from different clusters. The second step has been to find the classification rules that are implied by cluster analysis. That is, we had to determine a set of logic and linguistic rules, that were a faithful and parsimonious translation of the numeric clusters obtained in the first phase. The necessity of the second phase is due to the fact that, after all, the journal quality is a political assessment. As political topic, it must be explained and defended with qualitative arguments, on which one may agree or disagree, rather than on numeric justifications such as distance functions.

Our two-step method can be described also in the following way. The first step is an inductive step and determines the most homogeneous clusters that are hidden behind the data. The second step is a deductive step and determines the rule of classification tree (Breiman, Friedman, Stone, and Olshen 1984) that best describes clusters. One may view the second step as the validation phase of cluster analysis, that is to determine the clusters structure. It is a step for which each discipline has its own methodology, but the general approach of using logical rules has been suggested by Drobics, Bodenhofer, and Winiwarter (2002).

Our analysis shows that mathematics journals can be clustered into 4 subsets, depending on two underlying properties. One is the journal prestige, as expected, but the other is the journal diffusion among economists. In other words, strict mathematics journals are separated from journals of applied mathematics to economics or finance.

2. The Fuzzy c-Partition of Qualitative Data

2.1 Journal Selection

The journals were selected by the committee, asking AMASES associates opinion in a free and open discussion, with the only formal requirement that the journal should be contained in at least one of the following research engines: *MathSciNet* (www.ams.org/mathscinet), *EconLit*, (www.econlit.org/index.html) and *Zentralblatt* (www.emis.de/ZMATH). At the end, the list included 138 scientific journals that covered a wide range of mathematics and economics subfields. A quick classification showed that the list is composed of Economics journals(23.2%), Finance and Insurance (17.4%), Statistics and Probability (9.4%), Operations Research (OR, 16.7%), Games and Decisions (GD, 4.3%), and Mathematics (M, 29.0%).

There were big differences between journals. First, they covered different fields, e.g "Set Valued Analysis" and "Computational Economics" are completely different journals, and then high quality publications like "Econometrica" and "Mathematics of Operations research" were next to "Theory and decisions" and "Utilitas Mathematica". Therefore a natural step of the process was to give a formal assessment of journal quality and relevance to the scope of the association. As discussed in the introduction, the Committee member - author of this paper - was aware of the benefits, but also of the shortcomings, of both impact factor and peer review methods. But journal quality assessment is a task that has been implemented by many other international scientific organizations. Many lists were available through the Internet and they had two clear advantages: they contain peer review opinions that are not flawed by personal interests or strategic behavior. Therefore the committee member agreed on surveying those lists and analyze them with statistical procedures.

The rankings that were selected from the original web-pages were the following:

- WU Wien journal rating: List developed by the Wirthshaftsuniversität Wien - Vienna University of Economics and Business Administration, in the document dated 9/18/2002.
- Liste des révues academiques établie par la direction de recherche du groupe HEC - Hautes Etudes Commerciales, document dated October 2003.

The following rankings were taken from the Harzing data base. The Harzing data base is a collection of ranking and assessments publicly available in the Harzing's web page. We took our data from the document "Journal Quality List", 16^{th} edition, 13 November 2005. The organizations and years that were considered are:

- AST 2003 (United Kingdom, Aston University). An opinion survey of academics of the Midlands universities.
- UQ 2003 (Australia, University of Queensland), an official list of 588 journals in six discipline clusters.
- VHB 2003(Germany, Austria and Switzerland). Ranking coming from

the Association of Professors of Management in German speaking countries.

- CRA 2005: (United Kingdom, Cranfield School of Management). The list provides guidelines on which journal to submit papers to be considered for grants applications.
- ESS 2005 (France, Ecole Superieure de Sciences Economiques et Commerciales).

2.2 Building the Data Base

The common feature of every ranking is that journals are classified into ordinal tiers, according to their importance, but many data are missing. The reasons for missing data may be that the journal is not important, e.g. a local journal, but it can also be the case that it not considered relevant by a scientific community, even if it is an outstanding journal for other disciplines. For statistical analysis, two kinds of data are to be considered: data are ordinal if they are available, e.g. the tiers ”A”, ”B” and ”C”, but data are qualitative if the assessment is not available, e.g. ”missing” or ”not missing”.

More formally, each journal is a statistical unit represented by a vector of 7 entries: $x_i = [x_{i1}, ..., x_{ij}, ..., x_{i7}]$ in which entry x_{ij} describes the evaluation expressed by Committee j, or the definition of ”missing”. In the data base, missing data constituted the overwhelming majority of cases, 63$\%$ of the entries. This is a problem encountered also in Mingers and Harzing (2006), which has been solved by estimating all missing data using logistic regression. But in our application, filling the matrix with estimations would strongly bias our research, since more than two thirds of data would be artificial.

We decided to treat all data as qualitative statements, then to use a qualitative index to measure observation distances. Let x_w and x_k be two journal profiles, let $d_j(x_w, x_k) = 1$ if $x_{wj} \neq x_{kj}$, $d_j(x_w, x_k) = 0$ otherwise, then the distance $d(x_w, x_k)$ between x_w and x_k is:

$$d(x_w, x_k) = \sum_{j=1}^{7} d_j(x_w, x_k).$$

The measure counts how many times two journals received different evaluations. For example, consider a subspace of two surveys with tiers 1 = good, 2 = fair, 3 = sufficient, M = missing. Consider the following five journals: $x_1 = [1, 1]$; $x_2 = [2, 2]$; $x_3 = [3, 3]$; $x_4 = [1, 2]$; $x_5 = [1, M]$. Then $d(x_1, x_2) = d(x_1, x_3) = d(x_2, x_3) = 2$ and $d(x_5, x_4) = d(x_1, x_4) = d(x_1, x_5) = 1$. If cluster analysis is applied to those data, homogeneous clusters will be formed by journals that receive the same evaluation, qualitative or quantitative, by all surveys, e.g. one cluster with all "good" evaluations, one cluster with all "fair" evaluations, and so on.

2.3 The Fuzzy c-partition of Qualitative Data

We will describe the optimization model and the algorithm that are used to find the journal clusters. Note that the range of the distance function is the integer numbers, therefore it is probable that some journals have the same distance to two or more clusters. In this case the cluster method should determine both clusters and the ambiguous data, e.g. journals that do not fit well in any cluster, or have the same distance to more than one cluster. The fuzzy c-clustering method (Bezdeh, Keller, Krisnapuram, Pal 2005) has the property that its outputs are:

- A set of centroids, which represents the typical features of members of that class.
- A set of similarity measures, or fuzzy membership functions, that explain the similiarity between an item, e.g a journal, and cluster centroids.

The Fuzzy c-Clustering Problem is an optimization model that can be stated as follows. A set of m patterns - or objects - $x_i, i = 1, ..., m$ is given. Each pattern is a n -dimensional vector. Each vector entry ranges over the discrete finite domain $Q = \{q_1, ..., q_k, ...\}$, so that $x_i \in Q^n$. In the following, $x_{ij} = q_k$ if and only if entry j of vector i is equal to q_k. The c-partition - or c-clustering - problem is to determine the best set of c centroids $v_j, j = 1, ..., c$ - or prototypes, or stereotypes - that represents the whole data set. Moreover, a set of weights $w_{ij}, i = 1, ..., m; j = 1, ..., c$ must be calculated, where the weight w_{ij} represents the observation i fuzzy membership function to class j, that is the class represented by centroid v_j. Weights w_{ij} are such that $0 \leq w_{ij} \leq 1$. If $w_{ij} = 1$, then pattern x_i belongs to class j; if $w_{ij} = 0$, then pattern i does not belong to class j. Values of w_{ij} ranging from 0 to 1 reflect the uncertainty of assigning pattern i to cluster j. Using this membership function, outliers have limited influence on centroid features and ambiguous data can be detected.

The Fuzzy c-Clustering Problem is formulated as follows (problem **P1**):

$$\min_{w,v} \sum_{j=1}^{c} \sum_{i=1}^{m} w_{ij}^{p} d(x_i, v_j), \tag{1}$$

$$\sum_{j=1}^{c} w_{ij} = 1, \text{ for every } i, \tag{2}$$

$$w_{ij} \geq 0 \text{ for every } i, j. \tag{3}$$

Note that p, $p \geq 1$, is the parameter controlling the system "fuzziness". If $p = 1$, then w_{ij} can be equal to 0 or to 1 (the standard "crisp" partition is obtained). If p increases, then uncertainty increases and data that are further away from any cluster are assigned with uniform weights w_{ij}. More formally, if centroids v_j are fixed, then optimal w_{ij} are calculated as:

$$w_{ij} = \frac{d(x_i, v_j)^{-\frac{1}{p-1}}}{\sum_{k=1}^{c} d(x_i, v_k)^{-\frac{1}{p-1}}}.$$

Conversely, if weights w_{ij} are fixed, then optimal centroids v_j can be calculated using the mode of each cluster (Benati 2008; Ng and Wong 2002). These properties are important to develop heuristic algorithms to solve problem **P1**, as is tested in Benati (2008). The basic subroutine alternates between two steps.

Fuzzy c-modes - or descending - subroutine.

Input: A centroid set $V^0 = \{v_1, ..., v_c\}$. Set $t \leftarrow 0$.

Step 1. *Optimal weights:* For the given set V^t, calculate the optimal weights w_{ij}^t.

Step 2. *Optimal centroids:* For the given weights w_{ij}^t, calculate the optimal centroids V^{t+1}.

Step 3. *Stopping rule:* If $V^{t+1} = V^t$, then V^{t+1} is a local optimum, calculate $f(V^t)$ and STOP, otherwise $t \leftarrow t + 1$, go to step 1.

It can be shown that the objective function decreases as t increases, so that the last centroid set V^t is a local optimum. Weights and centroids are optimal with respect to each other, but it cannot be guaranteed that the global minimum has been reached. There are many methods to improve the incumbent solution. In Belacel, Hansen and Mladenovic (2002), a fast interchange "add-drop" heuristic has been proposed to improve the local optimum. The less meaningful centroid is discarded and replaced by a new one. Then the descending subroutine is applied again. Moreover, the solution space must be visited even in domain regions that are farther away from local optima. For the problem at hand, various local search techniques, such has tabu search, variable neighborhood search and candidate list search, are tested in Benati (2008) and they all strongly outperform the random restart algorithm. In this application we found that the best method to cluster data has been the Variable Neighborhood Search algorithm.

3. Classification Results

We used the algorithm ”Variable Neighborhood Search” described in Benati (2008). Different values of p and c were tested and the most clear results were obtained with $p = 1.8$ and $c = 4$. Crisp clusters are obtained from fuzzy clusters assigning journal i to the centroid j with the highest weight w_{ij}, but, if two or more centroids attain almost the same maximum, that is with a difference of 0.01 between weights w_{ij}, than that journal falls into the ”Ambiguous Data” category and it is not assigned to any cluster. Group compositions are listed in Appendix 1. The groups that were attained can be described as follows:

- **Group 1**. It is composed of 17 important and widespread journals. The group centroid is a journal that is highly ranked (A and A+) from all surveys with the exception of the UQ-2003, for which there is a missing data. The most striking feature of this group is the number of economics and financial journals, that is 14, with respect to mathematics ones, that are only 3. Those journals are Management Science, Operations Research and Journal of the American Statistical Association.
- **Group 2**. It is composed of 21 widespread journals, but with rankings below group 1. The group centroid is a journal that is ranked below the highest rating by all surveys, with the exception of the UQ-2003, for which there is a missing data. Again, this cluster is composed for the greatest part by economics or financial journal. Among the mathematics journals there are European Journal of Operational Research, Annals of Operations Research and Journal of the Operational Research Society.
- **Group 3**. It is composed of 34 good ranked journals. The group centroid is a journal evaluated only by the WU survey with the A ranking[2]. The group is composed by many mathematics journals, that are less general than the ones that are contained in the first two groups, for example Journal of Global Optimization and Fuzzy Sets and Systems belong to this cluster. But it also contains economics journals that are less relevant than the ones of the first two groups, e.g. Resource and Energy Economics or Computational and Mathematical Organization Theory are in group 3.
- **Group 4**. The last group, composed of 43 items, contains the journals that were selected by the AMASES committee, but they were not ranked by any surveys of the Harzing data base. The group centroid

2. The WU tiers are A+, A, B and C.

is a journal that is characterized by a vector of all missing data. The cluster is composed mainly by mathematics journals.

Note that clusters do not correspond strictly to the ordinal ranking. For example, group 1 is better than group 2, but the difference between group 2 and 3 is that journals in group 2 are more popular than the ones in 3. So, it can be sustained that journals are clustered according to two main features. The first feature separates applied mathematics journal to economics and finance from the other mathematics journals: e.g. the applications to economics are clustered in the first two groups. Then, journal rating plays a role: the assessments that characterized the second groups are all less than the assessments that characterized the first group.

There is an heterogeneous group of journals, for a total of 23 titles, that are not contained in any of the previous clusters, because they have the same distance to two or more groups. Some journals are in the middle between group 3 and group 2. That is, they are prestigious mathematics journals, but are not evaluated by a sufficient number of committees, for example, Mathematics of Operations Research and Naval Research Logistic. The other source of ambiguity is the case in which mathematics journals are evaluated only by the WU survey, but with different ranking with respect to journals of group 3, for example Theory and Decisions and Optimization Methods and Software are ranked B instead of A, e.g. they are in the middle between group 3 and 4. Then there are journals that are in the middle between group 1 and 2, e.g. European Economic Review. In the following section we will describe how to resolve this ambiguity, once that we have a clear definition of what journals are contained in a cluster.

3.1 Cluster Definition

The cluster structure that has been obtained in the first phase of the analysis, revealed that journals are clustered according to prestige and diffusion. The two features are correlated, but not dependent: mathematics journals are less surveyed than economics ones. In the second phase of the analysis we wish to find the set of logical rules that were able to replicate the clusters. The reason for this phase of the analysis is to define clusters more clearly. The distance function that is used in cluster analysis is a good trick to discover hidden patterns, but cannot define and validate clusters by itself, e.g. it does not explain why journals belong to clusters. On the second hand, logical rules are useful to resolve the ambiguous journal to belong to some cluster, or to define new groups, that distance matrix was not able to detect, but that are coherent with the hidden rules.

To classify journals, the following statistics are needed. $NZ(i)$ is the number of surveys that assessed journal i. $WU(i)$ is the assessment of i by the WU survey. $AV(i)$ is the average of the assessments[3] of all surveys. Only three questions are needed to classify data, but answers depend on some parameters that we tried to optimize. We select those values according to the less number of journals that were not correctly classified.

Step 1: How many times the journal has been assessed?

- If $NZ(i) = 0$ then journal i belongs to group 4.
- If $1 \leq NZ(i) \leq 4$ then go to the Step 2.
- If $NZ(i) > 4$ then go to step 3.

Step 2: What is the assesmemt of the WU survey?

- If $WU(i) = A$, then journal i belongs to group 3.
- If $WU(i) \neq A$, then journal i is labeled *ambiguous*.

Step 3: What is the average of the assessments?

- If $AV(i) < 1.5$, then journal i belongs to group 1.
- If $1.5 \leq AV(i) \leq 1.6$, then the journal is labeled ambiguous.
- If $AV(i) > 1.6$, then the journal belongs to group 2.

Using these rules, we were able to obtain data clusters that are very similar to the ones that are obtained by the fuzzy algorithm: 127 out of 138 journals are correctly assigned to the same group as before, only 11 journals were misplaced.

Those rules show that ambiguous journals are obtained either in Step 2, in the case that the WU survey assessment is different from A, or in step 3, in the case that journal i receives an intermediate judgement between group 1 and 2. Therefore classification rules can be modified and improved adding two more answers to step 2, e.g. $WU(i) = A+$ and $WU(i) = B$, and resolving the ambiguity in step 3, e.g $1.5 \leq WU(i) \leq 1.6$ in one direction.

It is worth noting that our classication could not result from the Impact Factor analysis. Using 2008 data, we obtained the following table of average IFs.

Cluster Impact Factor

	Impact Factor
Cluster 1	2.5635
Cluster 2	1.2035
Cluster 3	0.9472
Cluster 4	0.9258

In cluster 1, IFs are high because they are economics journals, while IFs in cluster 2, 3 and 4 largely overlaps. This suggests that the IF alone does not reveal the structure of the AMASES list.

3. Ordinal data are turned into cardinal data using the scale 1 = best tier, 2 = second best tier, and so on.

4. Conclusion

Our analysis shows how to use peer reviews to reveal journal clusters. The resulting clusters do not strictly correspond to ordinal tiers, but this property is required in all cases in which journals do not belong all to the same field. In our case, revealed tiers are biased by journal popularity. Actual bibliometric indexes do not consider the possibility that a journal does not strictly belong to a well defined field, but it is located on the border between two disciplines. We think that future research on bibliometric indexes should establish the degree to which field a journal belongs, and here fuzzy membership measure could be more appropriate than 0-1 values. With this information, citation indexes will be surely more meaningful.

Appendix: The Journal Clusters

Here is the list of journals, grouped according to the fuzzy clustering algorithm.

Group 1

American Economic Review
Econometrica
Journal of Business
Journal of Econometrics
Journal of Economic Theory
Journal of Finance
Journal of Financial and Quantitative Analysis
Journal of Financial Economics
Journal of Monetary Economics
Journal of Political Economy
Journal of the American Statistical Association
Management Science
Operations Research
Quarterly Journal of Economics
Rand Journal of Economics
Review of Economic Studies
Review of Financial Studies

Group 2

Annals of Operations Research
Applied Mathematical Finance
Economic Journal
Economics Letters
Environment and Planning
European Journal of Operations Research
Geneva Papers on Risk and Insurance Theory
International Economic Review
International Journal of Game Theory
Journal of Operations Management
Journal of the Operational Research Society
Journal of Banking and Finance
Journal of Derivatives
Journal of Economic Behaviour and Organization
Journal of Environmental Economics and Management
Journal of Futures Markets
Journal of Public Economics
Journal of Risk and Insurance
Journal of Risk and Uncertainty
Mathematical Finance
OMEGA International Journal of Management Science

Group 3

Advances in Applied Probability
American Statistician
Computational and Mathematical Organization Theory
Computational Optimization and Applications
Discrete Mathematics
Environmental and Resource Economics
European Journal of Finance
European Journal of Political Economy
Finance and Stochastics
Fuzzy Sets and Systems
Games and Economic Behaviour
Journal of Information and Optimization Science
Journal of Applied Probability
Journal of Global Optimization
Journal of Mathematical Analysis and Applications
Journal of Mathematical Economics
Journal of Optimization Theory and Applications
Linear Algebra and its Applications
Macroeconomic Dynamics

Group 3 continued

Mathematical Social Sciences
Operations Research Letters
Optimization
Resource and Energy Economics
Review of Derivative Research
Scandinavian Actuarial Journal
SIAM Journal Mathematic Analysis
SIAM Journal Matrix Analysis
SIAM Journal of Applied Mathematics
SIAM Journal on Control and Optimization
SIAM Journal on Optimization
Statistics and Probability Letters
Stochastic Analysis and Applications
Stochastic Processes and their Applications
Theory of Probability and its Applications

Group 4

Applied Mathematical Modelling
Applied Stochastic Models in Business and Industry
ASIA Pacific Journal of Operation Research
ASTIN Bulletin
Bl. Dtsch. Ges. Versicherungsmath
Calculus of Variations and Partial Differential Equations
Chaos
Communications on pure and applied analisys
Communications on pure and applied mathematics
Control and Cybernetics
Decisions in Economics and Finance
Differential Equations and Dynamical Systems
Ergodic Theory and Dynamical Systems
European Journal of Applied Mathematics
Function Analysis and its application
International Journal of Applied and Theoretical Finance
International Journal of Bifurcation and Chaos in Applied Sciences and Engineering
International Journal of Computation and numerical analysis and applications
Journal Convex Analysis
Journal de Mathematiques Pures et Appliques
Journal of the Operations Research Society of Japan
Journal of Pure and Applied Algebra
Journal of Actuarial Practice
Journal of Differential Equations
Journal of Dynamics and Differential Equations
Journal of Evolution Equations
Journal of Non Linear Science
Journal of Public Economic Theory
Mathematical and Computer Modelling
Networks
Nonlinear Analysis: Real World Applications
Nonlinear Analysis: Theory, Methods and Applications
North American Actuarial Journal
Numerical Functional Analysis and Optimization
Optimal Control Applications and Methods
Positivity
Quantitative Finance
RAIRO Recherce Operationalle
Review of Economic Design
Schweizerische Vereinigung der Versicheriung-mathematiker Mitteilungen
Set Valued Anal
Stochastics and Stochastic Report
Utilitas Mathematica

Ambiguous data

Annals of Applied Probability
Annals of Probability
Annals of Statistics
Applied Mathematics and Optimization
Computational Economics
Economic Modelling
Economic Theory
European Economic Review/ Journal of European Economic Association
Insurance Mathematics and Economics
International Game Theory Review
Journal of Economic Dynamics and Control
Journal of Evolutionary Economics
Mathematical Methods of Operations Research
Mathematical Programming
Mathematics and Computers in Simulation
Mathematics of Operations Research
Naval Research Logistics
Optimisation Method and Software
Or Sxpectrum
Review of Economics and Statistics
SIAM Review
Theory and Decision
Transportation Research B

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