Sebastia Massanet
Susana Montes
Daniel Ruiz-Aguilera
Manuel González-Hidalgo (Eds.)

LNCS 14069

Fuzzy Logic and Technology, and Aggregation Operators

13th Conference of the European Society for Fuzzy Logic and Technology, EUSFLAT 2023, and 12th International Summer School on Aggregation Operators, AGOP 2023
Palma de Mallorca, Spain, September 4–8, 2023, Proceedings

Springer

MOREMEDIA

Lecture Notes in Computer Science **14069**

Founding Editors

Gerhard Goos
Juris Hartmanis

Editorial Board Members

Elisa Bertino, *Purdue University, West Lafayette, IN, USA*
Wen Gao, *Peking University, Beijing, China*
Bernhard Steffen, *TU Dortmund University, Dortmund, Germany*
Moti Yung, *Columbia University, New York, NY, USA*

The series Lecture Notes in Computer Science (LNCS), including its subseries Lecture Notes in Artificial Intelligence (LNAI) and Lecture Notes in Bioinformatics (LNBI), has established itself as a medium for the publication of new developments in computer science and information technology research, teaching, and education.

LNCS enjoys close cooperation with the computer science R & D community, the series counts many renowned academics among its volume editors and paper authors, and collaborates with prestigious societies. Its mission is to serve this international community by providing an invaluable service, mainly focused on the publication of conference and workshop proceedings and postproceedings. LNCS commenced publication in 1973.

Sebastia Massanet · Susana Montes ·
Daniel Ruiz-Aguilera ·
Manuel González-Hidalgo
Editors

Fuzzy Logic and Technology, and Aggregation Operators

13th Conference of the European Society for Fuzzy Logic and Technology, EUSFLAT 2023, and 12th International Summer School on Aggregation Operators, AGOP 2023
Palma de Mallorca, Spain, September 4–8, 2023
Proceedings

Springer

Editors
Sebastia Massanet
University of the Balearic Islands
Palma, Spain

Susana Montes
University of Oviedo
Gijón, Spain

Daniel Ruiz-Aguilera
University of the Balearic Islands
Palma, Spain

Manuel González-Hidalgo
University of the Balearic Islands
Palma, Spain

ISSN 0302-9743 ISSN 1611-3349 (electronic)
Lecture Notes in Computer Science
ISBN 978-3-031-39964-0 ISBN 978-3-031-39965-7 (eBook)
https://doi.org/10.1007/978-3-031-39965-7

© The Editor(s) (if applicable) and The Author(s), under exclusive license
to Springer Nature Switzerland AG 2023

This work is subject to copyright. All rights are reserved by the Publisher, whether the whole or part of the material is concerned, specifically the rights of translation, reprinting, reuse of illustrations, recitation, broadcasting, reproduction on microfilms or in any other physical way, and transmission or information storage and retrieval, electronic adaptation, computer software, or by similar or dissimilar methodology now known or hereafter developed.
The use of general descriptive names, registered names, trademarks, service marks, etc. in this publication does not imply, even in the absence of a specific statement, that such names are exempt from the relevant protective laws and regulations and therefore free for general use.
The publisher, the authors, and the editors are safe to assume that the advice and information in this book are believed to be true and accurate at the date of publication. Neither the publisher nor the authors or the editors give a warranty, expressed or implied, with respect to the material contained herein or for any errors or omissions that may have been made. The publisher remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

This Springer imprint is published by the registered company Springer Nature Switzerland AG
The registered company address is: Gewerbestrasse 11, 6330 Cham, Switzerland

Preface

Almost 24 years ago, the 1999 EUSFLAT-ESTYLF Joint Conference was held in Palma. This conference, which took place from September 22 to 25, 1999, was organized by the University of the Balearic Islands and the European Society for Fuzzy Logic and Technology (EUSFLAT) and it was the first edition of the conferences of this society, after its foundation that same year. After the success of the first edition, this conference has been organized every two years in many European towns. Namely, Leicester (United Kingdom), Zittau (Germany), Barcelona and Gijon (Spain), Ostrava and Prague (Czech Republic), Lisbon (Portugal), Aix-Les-Bains (France), Milano (Italy), Warsaw (Poland) and Bratislava (Slovak Republic) have been the venue for subsequent editions. Now, on the eve of the 25th anniversary, it is time for the EUSFLAT conference to return to its origins, back to its roots.

The world has changed a lot since 1999. However, some facts remain stable. The aim of the conference, in line with the mission of the EUSFLAT Society, is to bring together theoreticians and practitioners working on fuzzy logic, fuzzy systems, soft computing, and related areas and to provide for them a platform for the exchange of ideas, discussing newest trends and networking. During these years and due to the successful development of fuzzy logic and the corresponding technology, interest in fuzzy logic has been growing steadily, and the EUSFLAT conference has been the main European conference in this scientific field. However, despite being a predominantly European conference, many researchers from other continents attend the EUSFLAT conferences edition after edition, recognizing that they constitute a reference point every two years for important advances in the lines of research associated with this field. In the specific case of the Balearic Islands, it should be noted that since the late 1980s intense research in fuzzy logic has been developed within the framework of the research group led by Gaspar Mayor and Joan Torrens, who are now happily retired. The new generation took the baton and the responsibility of organizing this edition of the EUSFLAT conference.

This 2023 edition of the EUSFLAT conference was co-located for the second time with two traditional events, namely with AGOP 2023 - International Summer School on Aggregation Operators; and with FQAS 2023 - International Conference on Flexible Query Answering Systems. We would like to express our thanks to the management of these events for sharing the vision of the joint multiconference. Special mention should be given to the AGOP summer school, with which these proceedings are shared. The AGOP summer school is organized biannually by the AGOP working group of EUSFLAT, reaching this year its 12th edition after its birth in 2001 in Oviedo (Spain). This event focuses on aggregation functions, a family of operators which have numerous applications, including, but not limited to, data fusion, statistics, image processing and decision making.

Therefore, this volume constitutes the proceedings of the 13th Conference of the European Society for Fuzzy Logic and Technology (EUSFLAT) and the 12th International Summer School on Aggregation Operators (AGOP). The papers included in the

proceedings volume have been subject to a thorough review process by at least two highly qualified peer reviewers, by using a single-blind process. The volume contains very attractive and up-to-date topics in fuzzy logic and related fields, which will result in significant interest of the international research communities active in the covered areas. Special gratitude is due to the extremely relevant role of the organizers of the special sessions. Thanks to their vision and hard work, we have been able to collect many papers on focused topics which we are sure will result, during the conference, in very interesting presentations and stimulating discussions at the sessions. It should be noted that for EUSFLAT and AGOP 2023, 71 full papers and 90 abstracts (161 submissions in total) were submitted from which 61 full papers have been accepted.

Finally, we would like to express our gratitude to all chairs and the organizing team for making these conferences possible. We believe that we will experience an excellent and unforgettable conference. We hope that you enjoyed it and that it brought home many new fruitful ideas for your research, and also that you enjoyed this beautiful island, Mallorca, the largest island in the Balearic Islands, set in the Mediterranean Sea, with its great beaches, amazing atmosphere and cultural richness.

September 2023

Sebastia Massanet
Susana Montes
Daniel Ruiz-Aguilera
Manuel González-Hidalgo

Contents

EUSFLAT General Track

The Inevitability of Vagueness in Fuzzy Logic 3
Marco Elio Tabacchi

A Fuzzy Cognitive Map Learning Approach for Coronary Artery Disease Diagnosis in Nuclear Medicine 14
Anna Feleki, Ioannis D. Apostolopoulos, Konstantinos Papageorgiou, Elpiniki I. Papageorgiou, Dimitris J. Apostolopoulos, and Nikolaos I. Papandrianos

Discussing Uninorms on Bounded Lattices Using Closure and Interior Operators 26
Gül Deniz Çaylı

Norms and Discrete Choquet Integrals Induced by Submodular Fuzzy Measures: A Discussion 39
Agnès Rico, Marie-Jeanne Lesot, and Christophe Marsala

Some Existence Results for Fuzzy Differential Equations with a Metric-Basic Derivative of Type (*ii*) 52
Mina Shahidi, Rosana Rodríguez-López, and Estevão Esmi

Elements of Relational Power Set Theories for Semiring-Valued Fuzzy Structures 61
Jiří Močkoř

Partial Fuzzy Relational Equations and the Dragonfly Operations – What Happens If...? 74
Nhung Cao and Martin Štěpnička

Conceptuality Degree of Oriented Crisply Generated Fuzzy Preconcepts 86
Alexander Šostak, Māris Krastiņš, and Ingrīda Uļjane

IFS-IBA Logical Aggregation with Frank t-norms 99
Pavle Milošević, Ivana Dragović, Milica Zukanović, Ana Poledica, and Bratislav Petrović

Fuzzy Equivalence Relations for Solving a Multiple Objective Linear Programming Problem 112
Olga Grigorenko and Mārtiņš Zemlītis

Applied Large-Scale Group Decision Making Using Systemic Consensus and Fuzzy Method of Comparative Linguistic Expressions 124
Benjamin Emmenegger, Georgiana Bigea, and Edy Portmann

Machine Learning and Fuzzy Measures: A Real Approach to Individual Classification 137
Inmaculada Gutiérrez, Daniel Santos, Javier Castro, Julio Alberto Hernández-Gonzalo, Daniel Gómez, and Rosa Espínola

Exploring the Automatic Selection of Aggregation Methods in Group Recommendation 149
Raciel Yera, Rosa M. Rodríguez, and Luis Martínez

Splitting Rules for Monotone Fuzzy Decision Trees 161
Christophe Marsala and Davide Petturiti

Root Cause Analysis with Fuzzy Cognitive Maps and Correlation Coefficient 174
Theodoros Tziolas, Konstantinos Papageorgiou, Theodosios Theodosiou, Aikaterini Rapti, Theofilos Mastos, Angelos Papadopoulos, and Elpiniki Papageorgiou

A Multi-criteria Group Decision-Making Method in Changeable Scenarios Based on Self-adjustment of Weights Using Reciprocal Preference Relations 185
José Ramón Trillo, Sergio Alonso, Ignacio Javier Pérez, Enrique Herrera-Viedma, Juan Antonio Morente-Molinera, and Francisco Javier Cabrerizo

Towards Imprecise Scores in Multi-criteria Decision Making with Ranked Weights 197
Pavel Novoa-Hernández, Boris Pérez-Cañedo, David A. Pelta, and José Luis Verdegay

A Multitask Deep Learning Approach for Staples and Wound Segmentation in Abdominal Post-surgical Images 208
Gabriel Moyà-Alcover, Miquel Miró-Nicolau, Marc Munar, and Manuel González-Hidalgo

FIDOC: A New Combination of Fuzzy Impulse Noise Detection and Open-Close Filtering 220
Peter Sussner and Manuel González-Hidalgo

Fuzzy Fingerprinting Large Pre-trained Models 232
Rui Ribeiro, Patrícia Pereira, Luísa Coheur, Helena Moniz, and Joao P. Carvalho

AGOP General Track

Aggregation Using Penalty and Moderate Deviation Functions 247
Jana Špirková and Juliana Beganová

An Interval-Valued Multi-attribute Decision Making Based on Combined QUALIFLEX-EAST Methodology 259
Debasmita Banerjee, Debashree Guha, Debjani Chakraborty, and Fateme Kouchakinejad

On an Edge Detector Based on Ordinal Sums of Conjunctive and Disjunctive Aggregation Functions 271
Marc Munar, Miroslav Hudec, Sebastia Massanet, Erika Mináriková, and Daniel Ruiz-Aguilera

SPECIAL SESSION 1: Interval Uncertainty

Why Fractional Fuzzy 285
Mehran Mazandarani, Olga Kosheleva, and Vladik Kreinovich

Interval-Valued and Set-Valued Extensions of Discrete Fuzzy Logics, Belnap Logic, and Color Optical Computing 297
Victor L. Timchenko, Yury P. Kondratenko, and Vladik Kreinovich

SPECIAL SESSION 2: Information Fusion Techniques Based on Aggregation Functions, Preaggregation Functions and Their Generalizations

Measuring the Distance Between Machine Learning Models Using F-Space ... 307
Mariam Taha and Vicenç Torra

On the Relationship Between Multidistances and n-Distances Revisited 320
Tomasa Calvo Sánchez and Pilar Fuster-Parra

Fuzzy Integrals for Edge Detection 330
C. Marco-Detchart, G. Lucca, G. Dimuro, T. Asmus, C. Lopez-Molina, E. Borges, J. A. Rincon, V. Julian, and H. Bustince

Transformation Techniques for Interval-Valued Intuitionistic Fuzzy Sets: Applications to Aggregation and Decision Making 342
José Carlos R. Alcantud and Gustavo Santos-García

SPECIAL SESSION 3: Evaluative Linguistic Expressions, Generalized Quantifiers and Applications

Verifying Validity of Selected Forms of Syllogisms with Intermediate Quantifiers Using Peterson's Rules 357
Petra Murinová and Vilém Novák

From Graded Aristotle's Hexagon to Graded Peterson's Hexagon of Opposition in Fuzzy Natural Logic 369
Petra Murinová and Stefania Boffa

Analysis of the Number of Valid Peterson's Syllogisms 381
Karel Fiala and Petra Murinová

Logical Relations Between T-Scaling Quantifiers and Their Implications in Fuzzy Relational Concept Analysis 393
Stefania Boffa and Petra Murinová

An Analysis of FRCA Quantifiers 405
Stefania Boffa and Brunella Gerla

SPECIAL SESSION 4: Neural Networks under Uncertainty and Imperfect Information

Arbitrariness of Outward Closeness in Laplacian Dimensionality Reduction . . . 419
Jiří Janeček and Irina Perfilieva

SPECIAL SESSION 5: Imprecision Modeling and Management in XAI Systems

Fuzzy Logic Function as a Post-hoc Explanator of the Nonlinear Classifier 431
Martin Klimo and Ľubomír Králik

A Bayesian Interpretation of Fuzzy C-Means 443
Corrado Mencar and Ciro Castiello

The Role of Speculations for Explainable and Trustworthy Artificial Intelligence: A Use Case on Art Genre Classification 455
Jose Maria Alonso-Moral and Vicent Costa

Fuzzy Sets: A Key Towards Hybrid Explainable Artificial Intelligence for Image Understanding 468
Isabelle Bloch

Contextual Boosting to Explainable SVM Classification 480
Marcelo Loor, Ana Tapia-Rosero, and Guy De Tré

SPECIAL SESSION 6: Recent Trends in Mathematical Fuzzy Logics

Ideals in the Two-Sorted Variety of Equational States 495
Serafina Lapenta, Sebastiano Napolitano, and Luca Spada

Maximal Theories of Product Logic 505
Valeria Giustarini and Sara Ugolini

Free Product Hoops 518
Francesco Manfucci and Sara Ugolini

A Logic to Reason About f-Indices of Inclusion over $Ł_n$ 530
Tommaso Flaminio, Lluis Godo, Nicolás Madrid, and Manuel Ojeda-Aciego

SPECIAL SESSION 7: Fuzzy Graph-Based Models: Theory and Application

Reduction Graph for Minimal Determinization of Fuzzy Automata 543
Aitor G. de Mendívil Grau, Stefan Stanimirović, and Federico Fariña

Finite Nerode Construction for Fuzzy Automata over the Product Algebra 555
Zorana Jančić, Ivana Micić, Stefan Stanimirović, Jose Ramón Gonzalez de Mendívil, and Miroslav Ćirić

Towards New Types of Weak Bisimulations for Fuzzy Automata Using the Product T-Norm 567
Ivana Micić, Jelena Matejić, Stefan Stanimirović, and Linh Anh Nguyen

On Relationships Between Approximate Bisimulations for Fuzzy Graphs and Their Approximation Degrees 579
Stefan Stanimirović, Ivana Micić, and Linh Anh Nguyen

SPECIAL SESSION 8: New frontiers of Computational Intelligence for Pervasive Healthcare Systems

An Information Extraction Study: Take in Mind the Tokenization! 593
Christos Theodoropoulos and Marie-Francine Moens

Early Parkinson's Disease Detection from EEG Traces Using Machine Learning Techniques 607
Lerina Aversano, Mario Luca Bernardi, Marta Cimitile, Martina Iammarino, Debora Montano, and Chiara Verdone

Cognitive Assistant for Physical Exercise Monitoring in Hand Rehabilitation 620
J. A. Rincon, C. Marco-Detchart, V. Julian, and C. Carrascosa

Interpretable Neuro-Fuzzy Models for Stress Prediction 630
Gabriella Casalino, Giovanna Castellano, and Gianluca Zaza

Explainable Deep Ensemble to Diagnose COVID-19 from CT Scans 642
Lerina Aversano, Mario Luca Bernardi, Marta Cimitile, Riccardo Pecori, and Chiara Verdone

SPECIAL SESSION 9: Fuzzy Implication Functions

A Study of Monometrics from Fuzzy Logic Connectives 657
Kavit Nanavati, Megha Gupta, and Balasubramaniam Jayaram

Monometrics on Lattice Betweenness Using Fuzzy Implications 667
Megha Gupta, Kavit Nanavati, and Balasubramaniam Jayaram

Fuzzy Implications Using Bandler-Kohout Subproduct 679
Katarzyna Miś, Kavit Nanavati, and Megha Gupta

The Form of Fuzzy Implication Functions Satisfying a Multiplicative Sincov's Equation 689
Michał Baczyński, Włodzimierz Fechner, Mateusz Pieszczek, and Sebastia Massanet

SPECIAL SESSION 10: New Challenges and Ideas in Statistical Inference and Data Analysis

Improved DE-MC Algorithm with Automated Outliers Detection 701
Kamila M. Rychlik and Maciej Romaniuk

A Specialized Xie-Beni Measure for Clustering with Adaptive Distance 713
Shidi Deng, Benoit Albert, Violaine Antoine, and Jonas Koko

Classification Error in Semi-Supervised Fuzzy C-Means 725
Kamil Kmita, Katarzyna Kaczmarek-Majer, and Olgierd Hryniewicz

A New Two-Sample Location Test for Fuzzy Data 737
Przemyslaw Grzegorzewski and Milena Zacharczuk

Author Index 749

Exploring the Automatic Selection of Aggregation Methods in Group Recommendation

Raciel Yera, Rosa M. Rodríguez, and Luis Martínez(✉)

Computer Science Department, University of Jaén, Jaén, Spain
martin@ujaen.es

Abstract. A recommender system is a software tool designed to support users to filter out useless options within a multitude of choices and provide them with the best possible ones. Group recommender systems have emerged as an important trend in recommendation since they recommend social items that are enjoyed by more than one individual, such as TV programs and travel packages, that are typically consumed in groups. Although algorithm selection in recommender systems is a research problem covered to some extent by the research community in which individuals' information is aggregated, this contribution is focused on the automatic selection of the most appropriate aggregation function in group recommendation. Specifically, a general framework that identifies group characteristics to be matched with the most appropriate aggregation function is presented. This approach is implemented by using a fuzzy decision tree classifier, in a content-based group recommendation approach. The development of an experimental protocol illustrates the advantage of the new proposal in relation to its corresponding baselines.

Keywords: group recommendation · fuzzy decision tree · preference aggregation

1 Introduction

The use of Recommender systems (RSs) is essential in online environments that concentrate on suggesting to users the items that most closely align with their preferences and requirements, given the overload of possible options in the product search space. Due to their functional principles, RSs have been extensively applied across a wide range of domains, including electronic commerce, e-learning, e-health, and e-tourism [14,20].

RSs have traditionally been employed to suggest items to individual users. Nonetheless, in recent times, different types of items, known as social items, that are often consumed by groups have emerged within recommendation contexts. Examples of such items include movies and tourist routes [7]. Recommending this kind of item entails an additional effort compared to individual recommendations, as preferences must be managed at both the individual and group level.

© The Author(s), under exclusive license to Springer Nature Switzerland AG 2023
S. Massanet et al. (Eds.): EUSFLAT 2023/AGOP 2023, LNCS 14069, pp. 149–160, 2023.
https://doi.org/10.1007/978-3-031-39965-7_13

This necessity has sparked the growth of Group Recommender Systems (GRSs) [7] as a separate research branch in the field of RSs.

Primarily, GRSs concentrate on processing the data linked to the members of a group. Such processing can be achieved by utilizing recommendation aggregation [8], where individual recommendations are initially calculated for each group member, and then combined via a recommendation aggregation method. Alternatively, a preference aggregation approach can also be employed [8], wherein a pseudo-user is generated that globally represents the group's preferences, and this pseudo-user profile is employed to compute the group recommendation. In both paradigms, aggregation is crucial in the recommendation process. Several authors such as De Pessemier et al. [8] have then incorporated different aggregation schemes such as Average (Avg), Least Misery (LM) or Most Pleasure (MP).

The current contribution concerns the automatic selection of the aggregation methods in group recommendation. The automatic selection of the most appropriate recommendation algorithm considering the nature of the data has been explored with some extent by the research community [6,17]. However, unlike to these research works focused on algorithm selection, our current contribution is focused on the selection of a suitable aggregator for the recommendation method. In addition, in contrast to the previous approaches centered on individuals, it is focused on group recommendation. Finally, we explore the use of fuzzy classification trees for managing the uncertainty associated to this scenario [21].

In this way, the current contribution aims at providing the following novelties:

- Developing a global methodology for performing an automatic selection of the aggregation function in group recommendation, based on the nature of the underlying group.
- The development of a working scenario for the application of the global methodology in a content-based group recommendation scenario.
- The execution of a experimental protocol for evaluating the impact of the proposed methodology in the working scenario.

The paper is structured as follows. Section 2 presents a background with an overview of the knowledge related to the proposal presentation, including group recommender systems, and automatic algorithm selection in recommender systems. Section 3 presents a general framework for automatic selection of aggregation functions in GRS. Section 4 illustrates a specific implementation of such framework, considering a fuzzy decision tree classifier and a content-based group recommendation approach. Section 5 evaluates such implementation, comparing it with associated baselines. Section 6 concludes the paper.

2 Preliminaries

The necessary background is provided here for the proposal discussion, focused on group recommendation and algorithm selection in RS.

2.1 Group Recommender Systems

RSs are AI-based systems used to provide users with the information that best fit their preferences and needs in overloaded search spaces [1]. The more spread taxonomy for identifying recommender systems, groups them into three main categories: 1) content-based recommender systems, 2) collaborative filtering-based recommender systems, and 3) hybrid recommender systems.

Herein, GRSs [8] have appeared as an emerging paradigm for scenarios in which recommended items are usually enjoyed by groups of users. Movies, touristic routes, or TV programs, are key examples of such kind of scenarios [14].

To perform item recommendations in such contexts by the content-based [16] or the collaborative filtering paradigm [8], the literature has identified two main recommendation techniques:

- *Rating aggregation:* The rating aggregation approach is based on the creation of a pseudo-user profile that represents the group's preferences [7,8]. This profile then receives the recommendation, using individual recommendation algorithms, as if it were a typical individual profile.
  To construct pseudo-user profiles, several aggregation strategies are commonly used, as described in [8]. Three of the most frequently used strategies include: 1) Average, which involves building the pseudo-user profile based on the average rating given by each member of the group for the corresponding item; 2) Least Misery, which involves building the pseudo-user profile based on the lowest rating given by any member of the group for the corresponding item; and 3) Most Pleasure, which involves building the pseudo-user profile based on the highest rating given by any member of the group for the corresponding item. These aggregation strategies are used to combine the ratings provided by individual members of the group to form a single profile that represents the group's preferences.
- *Recommendation aggregation:* This approach aggregates individual recommendations of each member of the group, to obtain the group's recommendation [8].
  In this scenario, the final stage of aggregation is based on the individual predictions made for each member of the group. There are three commonly used aggregation schemes for this purpose, as described in [8]. The first scheme is the Average approach, which involves calculating the group's prediction for a particular item as the average of the predicted ratings made by each individual user in the group for the same item. The second scheme is Least Misery, which determines the group's rating as the minimum of the predicted ratings made by each individual user. The third scheme is Most Pleasure, which determines the group's rating as the maximum of the predicted ratings made by each individual user. It is important to note that while these aggregation schemes are similar to the rating aggregation scheme, they have a different meaning in this context.

The current research work is focused on proposing a framework for facilitating the automatic selection of the aggregation measures, taking as base

the content-based group recommender system approach (CB-GRS) [16]. In this way, while the previous works focused on content-based group recommendation [13,16] incorporate the aggregation approaches based on a pre-defined viewpoint, the aim of our proposal is the automatic identification of the most appropriate aggregation approach tailored to the current group features.

2.2 Automatic Algorithm Selection in Recommender Systems

The automatic selection of the most suitable recommendation algorithm, based on the nature of the data, has been explored by the research community to some extent.

In an initial study, *the problem of selecting the most appropriate Collaborative Filtering (CF)* algorithm was explored by representing the data as a graph rather than a rating matrix [12]. The study derived metafeatures that are dependent on the graph to choose among nearest neighbor (NN) algorithms. Additionally, the selection process utilized a rules-based model that leveraged domain-specific knowledge.

Subsequent studies investigated the rating matrix by utilizing statistical and/or information-theoretical metafeatures to choose between nearest neighbor (NN) and matrix factorization (MF) algorithms [2]. In these studies, the task was approached as a regression problem, with the objective of improving the Root Mean Square Error (RMSE) performance.

A different technique, which involved a decision tree regression model, was later proposed to address the problem [9]. This method examined the connection between user ratings and neighborhood data, as well as the anticipated error in the recommendations provided by a nearest neighbor (NN) algorithm. Unlike previous approaches, this method concentrated on characterizing metafeatures for individual users instead of the entire dataset.

Furthermore, Cunha et al. [6] conducted an empirical study on algorithm selection for collaborative filtering, considering statistical features of the RS dataset and their impact on the performance of different CF approaches. More recently, Polatidis et al. [17] proposed a methodology for recommender system algorithm selection using a machine learning classifier, which indicated that tree-based approaches such as Decision Tree and Random Forest perform well and provide accurate and precise results.

Unlike previous works, our proposal focuses on selecting a specific aggregation operator of the recommendation method, rather than the algorithm as a whole. Moreover, it is focused on group recommendation, rather than individual recommendation as in previous studies.

3 A General Framework for Automatic Selection of the Aggregation Measure

A methodology for performing the automatic selection of the aggregation functions in group recommendation is presented here. Figure 1 depicts this method-

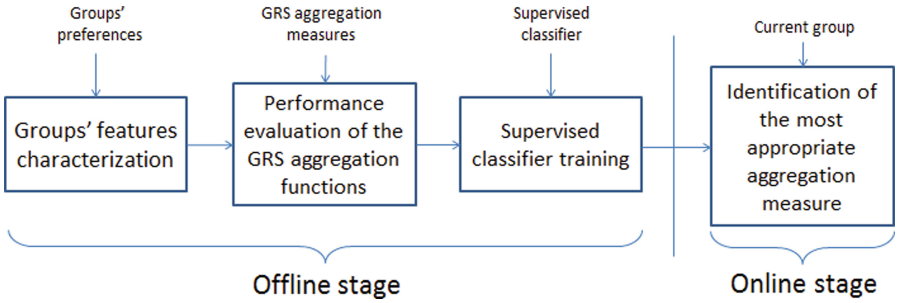

Fig. 1. General methodology for automatic selection of the aggregation function in GRS.

ology, which is composed of offline and online stages, and comprises the following steps:

1. **Group's features characterization:** It is focused on exploring groups' preferences values for extracting features that could be relevant for characterizing groups. Such features could be directly obtained from such values (e.g. rating averages, amount of ratings, the higher rating value), or depending of intermediate calculation such as the groups' member correlation values.
2. **Performance evaluation of the GRS aggregation functions:** It explores the performance of a selected GRS method, for each specific group and considering different aggregation functions. Here, the goal is to identify for each mentioned group, the aggregation function that performs best. As mentioned in Sect. 2, some of the aggregation measures usually considered in GRS are Average, Least Misery, and Most pleasure [8]. Here it is important to point out that in the next future it will be explored further power means and OWA operators at this stage [5]; however it is necessary to characterize better their behavior in the GRS context, before their use a part of an automatic selection strategy.
3. **Supervised classifier training:** It trains a supervised classifier for linking the features identified at Step 1, with the best aggregation functions identified at Step 2. This approach assummes the hypothesis that the performance of each aggregation function depends on the value of some group's features. Even though, these three stages have a low computational cost, they can be also executed in an offline phase, previously to the real-time recommendation generation process.
4. **Identification of the most appropriate aggregation function:** This step represents the online phase of the procedure. It is focused on the use of the classifier trained in the previous step, for identifying the most appropriate aggregation function that will be used for the active group, in the recommendation generation process.

The presented methodology can be implemented in different GRS and supervised classifiers scenarios, exploiting the benefits at each specific case. The fol-

lowing section will explore it, considering a content-based group recommendation approach and a fuzzy decision tree-based classifier.

4 Automatic Selection of the Aggregation Function in Content-Based Group Recommendation

This section illustrates the implementation of the methodology presented in the previous section, in a content-based group recommendation scenarios [16]

Group's Features Characterization: This step characterizes groups by using features with a clear semantic meaning, to facilitate the understanding of the classification procedure that will be used in the following steps.

The following group features are used:

- The minimum Pearson's correlation coefficient value between any pair of group members (M) (Eq. 1).

$$M(G) = min \;\; corr(u, v), \; \forall u, v \in G \tag{1}$$

- The amount of ratings linked to the group (A) (Eq. 2). $|R_u|$ is the number of preferences of user u.

$$A(G) = \sum_{u \in G} |R_u| \tag{2}$$

- The amount of items that have been co-evaluated by all the current group users (C) (Eq. 3).

$$C(G) = |I_c|, \; where \; I_c = \{i \; : \; \forall_{u \in G} r_{ui} \in R\} \tag{3}$$

- The rating average of the group (AV), formalized through Eqs. 4–5.

$$AV(G) = \frac{\sum_{r_{ui} \in R} r_{ui}}{|R|} \tag{4}$$

$$R = \cup_{u \in G} R_u \tag{5}$$

The selection of these features is based on previous work that raises the relevance of such information in the GRS context [4,8].

In the next step of the procedure, it will be assumed that the features are normalized into the interval $[0, 1]$.

Performance Evaluation of the GRS Aggregation Functions: This step will use the hybrid CB-GRS approach recently presented by Pérez-Almaguer et al. [16], and that comprises the following components, not detailed here due to space reasons:

1. A content-based item and user profiling stage, facilitating the use of the approach in cold-start scenarios.

2. The use of a weighting scheme for calculating the user-item matching values.
3. The addition of a virtual user profile to the group for boosting clear tendencies across the member's preferences.
4. The possibility of using the average or minimum aggregation, for aggregating the individual predicted preferences into the group preferences.

This method is executed over the groups considered across the whole process, using both the average and minimum aggregation approaches (Step 4). Taking into account a performance metric (in this case Precision [10]), the aggregation approach that performed best is stored for each group, using it as the class in the next supervised classifier building.

Supervised Classifier Training. Here we introduce the procedure to build the fuzzy decision tree, using the group features identified before.

Here the group G is represented by a membership value to the fuzzy set D, which is initially 1 for all the groups. In this context, G is identified through the corresponding values of the four attributes considered previously ($A_i \in \{M, A, C, AV\}$), as well as the value of the corresponding class ($C_k \in \{Average, Minimum\}$). D^{C_k} is a fuzzy subset of D, being $\mu_{D^{C_k}}(G) = \mu_D(G)$ whether G class is C_k, and $\mu_{D^{C_k}}(G) = 0$ in other case. $|D^{C_k}|$ is the cardinality of the fuzzy set D^{C_k}. [19].

For sake of simplicity, the numerical attribute A_i is featured by using three triangular fuzzy sets *low*, *medium*, and *high* (Fig. 2). Table 1 illustrates the group profiling process according to this viewpoint.

Table 1. Group profiling using the fuzzy sets *low*, *medium*, and *high*.

g_1	$(\mu_{M,low}(g_1),\mu_{M,medium}(g_1),\mu_{M,high}(g_1),\mu_{A,low}(g_1),\mu_{A,medium}(g_1),\mu_{A,high}(g_1),$ $\mu_{C,low}(g_1),\mu_{C,medium}(g_1),\mu_{C,high}(g_1),\mu_{AV,low}(g_1),\mu_{AV,medium}(g_1),\mu_{AV,high}(g_1))$
g_2	$(\mu_{M,low}(g_2),\mu_{M,medium}(g_2),\mu_{M,high}(g_2),\mu_{A,low}(g_2),\mu_{A,medium}(g_2),\mu_{A,high}(g_2),$ $\mu_{C,low}(g_2),\mu_{C,medium}(g_2),\mu_{C,high}(g_2),\mu_{AV,low}(g_2),\mu_{AV,medium}(g_2),\mu_{AV,high}(g_2))$
...	

The approach for the fuzzy decision tree induction comprises then the subsequent steps:

1. Construct a root node, as a fuzzy set D having the groups with 1 as membership value.
2. If a candidate node t with a fuzzy set of data D verifies that $\frac{|D^{C_k}|}{|D|} \geq \theta_r$, being $C_k \in \{Average, Minimum\}$; or $|D| \leq \theta_n$; or that all the features have been already analyzed, then the current node is a leaf, and its weight for each C_k is $|D^{C_k}|$. θ_r and θ_n are thresholds which values are empirically determined.
3. Otherwise, the new decision node is constructed as follows, by selecting the attribute that maximizes the information gain $G(A_i, D)$. Therefore, for each attribute $A_i \in \{M, A, C, AV\}$ not considered before, calculate the information

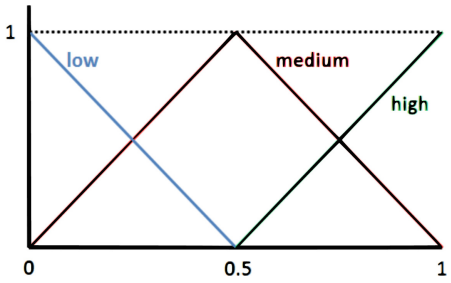

Fig. 2. Membership functions

gain $G(A_i, D)$ (Eqs. 6–9) and select the attribute A_{max} that maximizes it: $G(A_i, D) = I(D) - E(A_i, D)$ where,

$$I(D) = -\sum_{k=1}^{n}(p_k * log_2 p_k) \tag{6}$$

$$E(A_i, D) = \sum_{j=1}^{m}(p_{ij} * I(D_{A_i,j})) \tag{7}$$

$$p_k = \frac{|D^{C_k}|}{|D|} \tag{8}$$

$$p_{ij} = \frac{|D_{A_i,j}|}{\sum_{l=1}^{m}|D_{A_i,l}|} \tag{9}$$

Here $I(D)$ at Eq. (6) is the total entropy of certain dataset D, while $E(A_i, D)$ at Eq. (7) is the fuzzy classification entropy of the attribute A_i. p_k is the relative frequency of the class C_k in the dataset, and p_{ij} is the relative frequency of all objects within the branch associated to the corresponding linguistic label j and attribute A_i, into each class. $D_{A_i,j}$ is the fuzzy subset which membership is represented by the linguistic term $j \in \{low, medium, high\}$ linked to the group attribute $A_i \in \{M, A, C, AV\}$.

4. Once A_{max} is chosen, **the current D is divided into three fuzzy subsets** $D_{A_{max,low}}$, $D_{A_{max,medium}}$, **and** $D_{A_{max,high}}$, each subset for each linguistic label that characterizes such attribute. The membership value of each group g to $D_{A_{max},j}$ ($j \in \{low, medium, high\}$), is then the product of the membership value of g to D, and the value $\mu_{A_{max,j}}(g)$ associated to A_{max} in D.
5. Generate new nodes t_1, t_2, t_3 for fuzzy subsets $D_{A_{max,low}}$,$D_{A_{max,medium}}$, and $D_{A_{max,high}}$, labelling with each corresponding linguistic term $j \in \{low, medium, high\}$, to each edge that connect them with D.
6. For each fuzzy subset $D_{A_{max,low}}, D_{A_{max,medium}}, D_{A_{max,high}}$, repeat recursively this algorithm from step 2.

This induced fuzzy decision tree is used in the online phase of the proposal, for identifying the best aggregation function associated to a specific group.

Identification of the Most Appropriate Aggregation Function: The induced fuzzy decision tree is used for building classification rules, associated to each branch, with the format:

$$Rule\ R = \ If\ A_{i1}\ is\ j1\ and\ ...\ and\ If\ A_{in}\ is\ jn\ then\ Class = C_k\ with\ weight\ W_k \tag{10}$$

Here $A_{i1} \in \{M, A, C, AV\}$, $j1 \in \{low, medium, high\}$, and $C_k \in \{Average, Minimum\}$. The rule weight W_k is the sum of the membership of all objects of class k, at the associated leaf.

For a group g, the classification is performed as:

1. Matching degree: The following equation obtains the activation degree of the left part of the rule, for the current group:

$$\mu_R(g) = T(\mu_{A_{i1,j1}}(g), \mu_{A_{i2,j2}}(g), ..., \mu_{A_{in,jn}}(g)) \tag{11}$$

   where $\mu_{A_{i,j}}(g)$ is the membership degree of the value of the $A_i \in \{M, A, C, AV\}$ attribute for group g with the fuzzy set associated to the same attribute A_i and the linguistic term $j \in \{low, medium, high\}$. T is a T-norm [15].
2. Association degree: The association degree of g with each rule R, considering the class k is calculated as:

$$b_{Rk}(g) = T(\mu_R(g), W_k) \tag{12}$$

   T is a T-norm [15].
3. Confidence degree: At last, the confidence degree of each class, for a specific group g, is reached through the aggregation of the association degrees linked to all the analyzed rules. This final calculation is used through the use of a T-conorm T^* [15]:.

$$conf_k(g) = T^*(b_{1k}(g), b_{2k}(g), b_{3k}(g), ..., b_{Rk}(g)) \tag{13}$$

   The classification process assigns then to the group g, the class k that obtains the higher association degree.

5 Experiments

This section is focused on the evaluation of the approach discussed previously.

5.1 Experimental Protocol

This evaluation will use the following databases, previously employed in related works [16]:

– **Movielens 100K,** with 943 users, 1682 movies, and 100000 preferences in the interval $[1, 5]$ [11].

– **HetRec,** containing heterogeneous information, with 2213 users, 10197 movies, and 855K+ ratings. The ratings are also in the range $[1, 5]$ [3].

This evaluation process will be guided by the Precision metric (Eq. 14), frequently used in the RS evaluation [13]. For sake of space other evaluation criteria were not included here, but will be considered in the future research.

$$Precision = \frac{|recommended\ items \cap preferred\ items|}{|recommended\ items|} \tag{14}$$

Here it is used a preference threshold $r_{ui} \geq 4$, that is a usual criteria for this parameter [18].

We use the subsequent stages for performing the evaluation [4,10]:

1. Train and test sets are created following the random procedure commonly used in previous works [4,10].
2. We build user groups of different sizes, and the groups creation process is executed considering users with common preferences.
3. The method presented across the current paper is developed, for choosing the suitable aggregation scheme for each group.
4. For each group, we apply the CB-GRS approach proposed by Pérez-Almaguer et al. [16], using the selected aggregation function in each case.
5. The top n recommendation performance is measured with the Precision, by matching the recommendation output with the preferences in the test set. At last, the average precision is calculated for all the groups.

5.2 Results

Using the previous protocol, the proposal is evaluated with $\theta_r = 0.9$ and $\theta_n = 0.01$ as parameters. This means that the fuzzy decision tree induction is stopped if the relative frequency of a certain class exceeds 0.9, or if the current node cardinality is less than 0.01. The used group size were 4 (Movielens) and 3 (HetRec), and several sizes of the recommendation sets were considered (see Table 2).

This evaluation considers as baseline the hybrid proposal presented at [16], considering both Average and the Minimum approaches (avg and min, in Table 2), which are the state-of-art existing approaches that will be compared with the current proposal. In the context of the experimental steps presented in the previous section, Step 3 is omitted for the baseline evaluation. This step introduces the execution of the procedure discussed across this paper (dyn, in Table 2).

The results demonstrate that for both datasets, the proposal effectively identifies the optimal aggregation scheme to be used in a hybrid CB-GRS. This is evidenced by its significant outperformance of two baselines that consistently employ average and minimum aggregation.

Table 2. Performance of the proposal, in relation to previous works. Precision metric.

Dataset	top N	1	2	3	4	5	10
Movielens	avg (baseline)	0.5787	**0.5844**	0.5788	0.5684	0.5740	0.5681
Movielens	min (baseline)	0.5813	0.5725	0.5829	0.5841	0.5845	0.5754
Movielens	dyn	**0.6025**	0.5806	**0.5879**	**0.5844**	**0.5855**	**0.5760**
HetRec	avg (baseline)	0.5050	0.5075	0.5039	0.5000	0.5013	0.4957
HetRec	min (baseline)	0.5700	**0.5483**	0.5417	0.5358	0.5297	0.5080
HetRec	dyn	**0.5817**	**0.5483**	**0.5422**	**0.5363**	**0.5299**	**0.5083**

6 Conclusions

The automatic selection of the aggregation functions in GRS presented in this contribution has been initially implemented over the content-based group recommendation context, but it can also be applied to other group recommender systems. It aims to provide an automatic building of the recommendation system, which can lead to an improvement in recommendation accuracy. It is worthy to mention that most of the proposed approach can be executed offline, facilitating its deployment in recommender context with a high volume of information.

Our future work includes the exploration of new features as well as feature extraction algorithms to enrich the group profiling process. In addition, other classifiers such as deep learning-based, will be studied for the selection of the suitable aggregation approach.

Acknowledgements. This research is supported by the Research Project *ProyExcel_ 00257*, linked to the Andalucía Excellence Research Program. R.Yera is also supported by the Grants for the Re-qualification of the Spanish University System for 2021–2023 in the María Zambrano modality (UJAR10MZ).

References

1. Adomavicius, G., Tuzhilin, A.: Toward the next generation of recommender systems: a survey of the state-of-the-art and possible extensions. IEEE Trans. Knowl. Data Eng. **17**(6), 734–749 (2005)
2. Adomavicius, G., Zhang, J.: Impact of data characteristics on recommender systems performance. ACM Trans. Manage. Inf. Syst. (TMIS) **3**(1), 1–17 (2012)
3. Cantador, I., Brusilovsky, P., Kuflik, T.: Second workshop on information heterogeneity and fusion in recommender systems (HetRec 2011). In: Proceedings of the 5th ACM Conference on Recommender systems, RecSys 2011, ACM, New York, NY, USA (2011)
4. Castro, J., Yera, R., Martínez, L.: An empirical study of natural noise management in group recommendation systems. Decis. Support Syst. **94**, 1–11 (2017)

5. Chen, Z.S., Yang, L.L., Rodríguez, R.M., Xiong, S.H., Chin, K.S., Martínez, L.: Power-average-operator-based hybrid multiattribute online product recommendation model for consumer decision-making. Int. J. Intell. Syst. **36**(6), 2572–2617 (2021)
6. Cunha, T., Soares, C., de Carvalho, A.C.: Metalearning and recommender systems: a literature review and empirical study on the algorithm selection problem for collaborative filtering. Inf. Sci. **423**, 128–144 (2018)
7. Dara, S., Chowdary, C.R., Kumar, C.: A survey on group recommender systems. J. Intell. Inf. Syst. **54**(2), 271–295 (2020)
8. De Pessemier, T., Dooms, S., Martens, L.: Comparison of group recommendation algorithms. Multimed. Tools Appl. **72**, 2497–2541 (2014)
9. Griffith, J., O'Riordan, C., Sorensen, H.: Investigations into user rating information and predictive accuracy in a collaborative filtering domain. In: Proceedings of the 27th Annual ACM Symposium on Applied Computing, pp. 937–942 (2012)
10. Gunawardana, A., Shani, G.: A survey of accuracy evaluation metrics of recommendation tasks. J. Mach. Learn. Res. **10**, 2935–2962 (2009)
11. Harper, F.M., Konstan, J.A.: The Movielens datasets: history and context. ACM Trans. Interact. Intell. Syst. **5**(4), 19:1-19:19 (2015)
12. Huang, Z., Zeng, D.D.: Why does collaborative filtering work? transaction-based recommendation model validation and selection by analyzing bipartite random graphs. INFORMS J. Comput. **23**(1), 138–152 (2011)
13. Kaššák, O., Kompan, M., Bieliková, M.: Personalized hybrid recommendation for group of users: top-n multimedia recommender. Inf. Process. Manage. **52**(3), 459–477 (2016)
14. Lu, J., Wu, D., Mao, M., Wang, W., Zhang, G.: Recommender system application developments: a survey. Decis. Support Syst. **74**, 12–32 (2015)
15. Pedrycz, W.: Fuzzy Control and Fuzzy Systems. Research Studies Press Ltd. (1993)
16. Pérez-Almaguer, Y., Yera, R., Alzahrani, A.A., Martínez, L.: Content-based group recommender systems: a general taxonomy and further improvements. Expert Syst. Appl. **184**, 115444 (2021)
17. Polatidis, N., Kapetanakis, S., Pimenidis, E.: Recommender systems algorithm selection using machine learning. In: Iliadis, L., Macintyre, J., Jayne, C., Pimenidis, E. (eds.) EANN 2021. PINNS, vol. 3, pp. 477–487. Springer, Cham (2021). https://doi.org/10.1007/978-3-030-80568-5_39
18. Ricci, F., Rokach, L., Shapira, B.: Recommender systems: introduction and challenges. In: Ricci, F., Rokach, L., Shapira, B. (eds.) Recommender Systems Handbook, pp. 1–34. Springer, Boston, MA (2015). https://doi.org/10.1007/978-1-4899-7637-6_1
19. Umanol, M., et al.: Fuzzy decision trees by fuzzy ID3 algorithm and its application to diagnosis systems. In: Proceedings of 1994 IEEE 3rd International Fuzzy Systems Conference, pp. 2113–2118. IEEE (1994)
20. Yera, R., Alzahrani, A.A., Martinez, L.: Exploring post-hoc agnostic models for explainable cooking recipe recommendations. Knowl.-Based Syst. **251**, 109216 (2022)
21. Yera, R., Martinez, L.: Fuzzy tools in recommender systems: a survey. Int. J. Comput. Intell. Syst. **10**(1), 776 (2017)

Author Index

A
Albert, Benoit 713
Alcantud, José Carlos R. 342
Alonso, Sergio 185
Alonso-Moral, Jose Maria 455
Antoine, Violaine 713
Apostolopoulos, Dimitris J. 14
Apostolopoulos, Ioannis D. 14
Asmus, T. 330
Aversano, Lerina 607, 642

B
Baczyński, Michał 689
Banerjee, Debasmita 259
Beganová, Juliana 247
Bernardi, Mario Luca 607, 642
Bigea, Georgiana 124
Bloch, Isabelle 468
Boffa, Stefania 369, 393, 405
Borges, E. 330
Bustince, H. 330

C
Cabrerizo, Francisco Javier 185
Calvo Sánchez, Tomasa 320
Cao, Nhung 74
Carrascosa, C. 620
Carvalho, Joao P. 232
Casalino, Gabriella 630
Castellano, Giovanna 630
Castiello, Ciro 443
Castro, Javier 137
Çaylı, Gül Deniz 26
Chakraborty, Debjani 259
Cimitile, Marta 607, 642
Ćirić, Miroslav 555
Coheur, Luísa 232
Costa, Vicent 455

D
de Mendívil Grau, Aitor G. 543
De Tré, Guy 480
Deng, Shidi 713
Dimuro, G. 330
Dragović, Ivana 99

E
Emmenegger, Benjamin 124
Esmi, Estevão 52
Espínola, Rosa 137

F
Fariña, Federico 543
Fechner, Włodzimierz 689
Feleki, Anna 14
Fiala, Karel 381
Flaminio, Tommaso 530
Fuster-Parra, Pilar 320

G
Gerla, Brunella 405
Giustarini, Valeria 505
Godo, Lluis 530
Gómez, Daniel 137
Gonzalez de Mendívil, Jose Ramón 555
González-Hidalgo, Manuel 208, 220
Grigorenko, Olga 112
Grzegorzewski, Przemyslaw 737
Guha, Debashree 259
Gupta, Megha 657, 667, 679
Gutiérrez, Inmaculada 137

H
Hernández-Gonzalo, Julio Alberto 137
Herrera-Viedma, Enrique 185
Hryniewicz, Olgierd 725
Hudec, Miroslav 271

© The Editor(s) (if applicable) and The Author(s), under exclusive license to Springer Nature Switzerland AG 2023
S. Massanet et al. (Eds.): EUSFLAT 2023/AGOP 2023, LNCS 14069, pp. 749–751, 2023.
https://doi.org/10.1007/978-3-031-39965-7

I
Iammarino, Martina 607

J
Jančić, Zorana 555
Janeček, Jiří 419
Jayaram, Balasubramaniam 657, 667
Julian, V. 330, 620

K
Kaczmarek-Majer, Katarzyna 725
Klimo, Martin 431
Kmita, Kamil 725
Koko, Jonas 713
Kondratenko, Yury P. 297
Kosheleva, Olga 285
Kouchakinejad, Fateme 259
Králik, Ľubomír 431
Krastiņš, Māris 86
Kreinovich, Vladik 285, 297

L
Lapenta, Serafina 495
Lesot, Marie-Jeanne 39
Loor, Marcelo 480
Lopez-Molina, C. 330
Lucca, G. 330

M
Madrid, Nicolás 530
Manfucci, Francesco 518
Marco-Detchart, C. 330, 620
Marsala, Christophe 39, 161
Martínez, Luis 149
Massanet, Sebastia 271, 689
Mastos, Theofilos 174
Matejić, Jelena 567
Mazandarani, Mehran 285
Mencar, Corrado 443
Micić, Ivana 555, 567, 579
Milošević, Pavle 99
Mináriková, Erika 271
Miró-Nicolau, Miquel 208
Miś, Katarzyna 679
Močkoř, Jiří 61
Moens, Marie-Francine 593
Moniz, Helena 232
Montano, Debora 607
Morente-Molinera, Juan Antonio 185
Moyà-Alcover, Gabriel 208
Munar, Marc 208, 271
Murinová, Petra 357, 369, 381, 393

N
Nanavati, Kavit 657, 667, 679
Napolitano, Sebastiano 495
Nguyen, Linh Anh 567, 579
Novák, Vilém 357
Novoa-Hernández, Pavel 197

O
Ojeda-Aciego, Manuel 530

P
Papadopoulos, Angelos 174
Papageorgiou, Elpiniki I. 14
Papageorgiou, Elpiniki 174
Papageorgiou, Konstantinos 14, 174
Papandrianos, Nikolaos I. 14
Pecori, Riccardo 642
Pelta, David A. 197
Pereira, Patrícia 232
Pérez, Ignacio Javier 185
Pérez-Cañedo, Boris 197
Perfilieva, Irina 419
Petrović, Bratislav 99
Petturiti, Davide 161
Pieszczek, Mateusz 689
Poledica, Ana 99
Portmann, Edy 124

R
Rapti, Aikaterini 174
Ribeiro, Rui 232
Rico, Agnès 39
Rincon, J. A. 330, 620
Rodríguez, Rosa M. 149
Rodríguez-López, Rosana 52
Romaniuk, Maciej 701
Ruiz-Aguilera, Daniel 271
Rychlik, Kamila M. 701

S
Santos, Daniel 137
Santos-García, Gustavo 342
Shahidi, Mina 52
Šostak, Alexander 86
Spada, Luca 495

Špirková, Jana 247
Stanimirović, Stefan 543, 555, 567, 579
Štěpnička, Martin 74
Sussner, Peter 220

T
Tabacchi, Marco Elio 3
Taha, Mariam 307
Tapia-Rosero, Ana 480
Theodoropoulos, Christos 593
Theodosiou, Theodosios 174
Timchenko, Victor L. 297
Torra, Vicenç 307
Trillo, José Ramón 185
Tziolas, Theodoros 174

U
Ugolini, Sara 505, 518
Uļjane, Ingrīda 86

V
Verdegay, José Luis 197
Verdone, Chiara 607, 642

Y
Yera, Raciel 149

Z
Zacharczuk, Milena 737
Zaza, Gianluca 630
Zemlītis, Mārtiņš 112
Zukanović, Milica 99