A NEW VISUALIZATION FOR PREFERENCES EVOLUTION IN GROUP DECISION MAKING

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Consensus reaching processes (CRPs) in Group Decision Making (GDM) try to reach a mutual agreement among a group of decision makers before making a decision. To evaluate and understand the performance of a CRP is often complex due to, mainly, the presence of disagreement among decision makers. A clear, simple, correct and suitable visualization of the discussion consensus rounds is key for facilitating the analysis of such performance because, without a clear visualization, it is hard to understand the disagreements among experts. This paper proposes a new visualization related to experts' preferences and their evolution for CRPs based on the Principal Component Analysis (PCA).

Keywords: GDM; CRP; PCA

1. Introduction

Decision making is a quotidian process in daily life. In Group Decision Making (GDM) problems, several decision makers or experts, with their own attitudes and opinions, need to reach a common solution, selecting the best alternative/s of a set of possible solutions.

Classically, the GDM resolution process, consisted in gathering the experts' assessments and choosing the best alternative/s according to the group's view. Nevertheless, many real-world problems might require consensualted decisions that are not ensured by the previous GDM process. For this reason, consensus reaching processes (CRPs), in which individuals/experts discuss and modify their preferences to reach a collective agreement before making decisions, have become an increasingly prominent research topic in GDM problems.[1–3] The resolution of GDM problems applying CRPs requires to take into account several aspects such as: conflicts between experts, detect non-collaborative experts, identify experts whose opinions are similar, etc. According to these aspects, to analyse and understand the evolution of a CRP is not a simple task. The visualization of the experts who participate in a CRP would facilitate the interpretability of the process, identifying easily the experts' behaviour, the advantages and drawbacks of a CRP model and bring to light either the correct or incorrect performance of the CRP.

The visualization of the experts' preferences to guide consensus in GDM problems presents an important challenge and, according to this, several proposals have been introduced.[4–7] Nevertheless, these proposals presents several aspects that should be improved/modified. On the one hand, they solely consider one type of preference relation to provide the experts' assessments; fuzzy preference relations (FPR)[8] in[5–7] and decision matrix in,[4] despite experts can provide their opinions using distinct preference relations such as linguistic preference relation (LPR),[9] hesitant preference relation[10] (HPR) or hesitant linguistic fuzzy preference relation[11,12] (HLPR). On the other hand, the visualization should be easy to compute and understand, allowing to obtain as much information as possible in the shortest possible time to facilitate the CRP analysis task. Furthermore, many of these proposals, develop/use a software focuses only on the experts' visualization. Nevertheless, it would be adequate to include such visualization in a framework that allows to consider other aspects related to the CRP for understanding the whole process in a proper way.

As it was aforementioned, the experts' preferences can be represented by means of multiple preferences relations, i.e. matrices compound by several rows and cols, that would require a multi-dimensional visualization that the human beings are not able to understand. The Principal Component Analysis (PCA)[13] technique has been successfully used for dealing with this problematic, since it allows to reduce the dimensionality of a set of data.

This paper presents a new visualization for experts' preferences and their evolution in CRPs using the PCA to reduce the dimensionality of the data and showing the preferences in a 2-D visualization space. Such visualization is integrated and validated in AFRYCA,[14,15] an analytic framework able to carry out analyses and studies in GDM problems resolution. The proposal is organized as follows: Section 2 makes a brief review on GDM, CRP and PCA. Section 3 introduces the new visualization for experts' preferences based on PCA, Section 4 shows an illustrative example using the AFRYCA 2.0 framework.[14] Finally, conclusions are given in Section 5.

2. Preliminaries

This section reviews several concepts about GDM problems CRPs, as well the main features of the PCA.

2.1. *Group Decision Making*

GDM is a process in which several experts participate in the selection of a common solution for a decision making problem, composed by a set of alternatives. Formally, a GDM problem is characterized[16] by n alternatives, denoted by $X = \{x_1, x_2, \ldots, x_n\}$ defined by a finite set of k criteria, $C = \{c_1, c_2, \ldots, c_k\}$, and a group of m experts, $E = \{e_1, e_2, \ldots, e_m\}$, who express their preferences over the alternatives, trying to reach a common solution. Each expert $e_i \in E$ express his/her opinion over distinct alternatives using distinct preference structures. The most common preference structures are introduced below:

- *Preference relations*: In a preference relation, experts express their opinions by means of pairwise comparisons between alternatives. These preferences are usually represented by symmetric matrices whose dimension is $n \times n$. Some examples are: FPR,[8] LPR,[9] HPR[10] and HLPR.[11,12]
- *Decision matrices*: In a decision matrix, experts express their opinions for each alternative over each criterion in function of its utility. These preferences are represented by matrices that might not symmetric whose dimension is $n \times k$.

Once the experts' preferences are gathered the classical process to solve a GDM problem is composed by two phases:[17] (i) Aggregation phase: experts' preferences are aggregated to obtain a collective assessments for the alternatives, (ii) Exploitation phase: an alternative or a subset of alternatives will be selected as solution for the problem.

2.2. *Consensus Reaching Processes*

Classically, the selection process in a GDM problem cannot guarantee the agreement between experts. Hence, several experts can feel that their opinion have not been sufficiently taken into account.[3] For this reason, CRPs were incorporated in the GDM problem resolution. CRP is an iterative and dynamic process in which experts change their opinions, trying to get closer each other, in order to reach a high agreement level after several rounds of discussion.[3] A CRP is composed by four phases:

(1) Gathering preferences: The experts provide their preferences.
(2) Consensus measurement: The group consensus degree is computed.
(3) Consensus control: The consensus degree obtained is compared with a predefined value which represents the minimum value of acceptable agreement. If the consensus degree is greater than the threshold value, the group starts the selection process, but, another discussion round would be carried out.
(4) Consensus progress: To increase the level of agreement throughout the discussion rounds of the CRP, experts have to modify their preferences.

2.3. *Principal Component Analysis*

Principal component analysis[13] is a multivariate technique that analyses a set of data whose observations are described by several inter-correlated quantitative dependent variables. Its main objective is to extract the most relevant information from the data, representing such information as a set of orthogonal variables called principal components. Finally, the similarity of the data and variables is computed and visualized by a reduced dimensional representation (e.g. 2D point). Starting from a matrix X composed by the initial data, the process consists of:

(1) Standardise the data subtracting the mean for each attribute.
(2) Compute the variance-covariance matrix of X, denote by C.

$$tC = X^T \cdot X \tag{1}$$

where X^T denotes the transpose of X and t is a positive integer.

(3) Calculate the eigenvalues and eigenvector of C and select the r greater eigenvalues, being r the final data dimension.

$$C \cdot u = \lambda \cdot u \tag{2}$$

(4) Represent the data in a U space with r dimension through a linear projection matrix denoted by M.

$$U = M \cdot X \tag{3}$$

3. New Visualization For Experts' Preferences Evolution In GDM By Using PCA

It has been pointed out in Sec. 2.1, experts can provide their preferences using distinct preference structures in order to solve a GDM problem. These preferences structure are represented by a matrix P of changing dimension whose visualization might require a multi-dimensional representation hard to manage by human beings.

To visualize the experts' preferences in a interpretable way, we propose to utilize the PCA technique to reduce the dimensionality of the preferences into a 2 dimensional space. Taking into account that experts can use different preference structures to provide their preferences, a transformation of all of them into a decision matrix, denoted as X, by means of a dominance process[18] is carried out, being the preference structures processing the same for all the structures. The dominance values are noted as follows:

$$D_i = \{d_1^i, d_2^i, \ldots, d_n^i\} \quad i \in \{1, \ldots, m\} \tag{4}$$

Afterwards, the dominance vectors are standardised subtracting the arithmetic mean of such vector to its dominance values.

$$\begin{aligned} \overline{D_i} &= \{\overline{d^i}_1, \overline{d^i}_2, \ldots, \overline{d^i}_n\} \\ \text{where} \quad \overline{d_j^i} &= |d_j^i - \frac{1}{n}\sum_{k=1}^{n} d_k^i| \quad j,k \in \{1, \ldots, n\} \end{aligned} \tag{5}$$

Starting from the standardised dominance vectors $\overline{D_i}$, the matrix X is composed as follows:

$$C = \begin{bmatrix} \overline{c_1^1} & \ldots & \overline{c_n^1} \\ \vdots & \ddots & \vdots \\ \overline{c_1^m} & \ldots & \overline{c_n^m} \end{bmatrix} \tag{6}$$

Then, the variance-covariance matrix of X is computed (see Eq. 2), obtaining the C matrix. Applying the decomposition of C, two eigenvectors denoted by u and v are calculated such that they have the greatest eigenvalues λ_1 and λ_2.

$$\begin{aligned} C \cdot u &= \lambda_1 \cdot u \\ C \cdot v &= \lambda_2 \cdot v \end{aligned} \tag{7}$$

The eigenvalues represent the amount of information contained in each principal component and their respective eigenvectors represent the direction of the principal component. Notice that we select two eigenvectors since the preferences will be represented in a 2D-map.

The coordinates of each expert in the (u, v) plane are given by:

$$(\overline{D^i}u, \overline{D^i}v) \tag{8}$$

where $\overline{D^i}$ is the standardised dominance vector of the expert i in the original space.

This visualization process has been included in AFRYCA 2.0[14] to prove its good performance. This software provides different GDM problems and CRP model that facilitates the proposal incorporation. In addition, thanks to the architecture based on components in which the framework has been developed, such inclusion has been carried out easily.

4. Illustrative Example

In order to show the new proposal of visualization for experts' preferences in GDM, this section describes a GDM problem for selecting the best conference on Data Science in 2018, applying a CRP. The CRP simulation and the subsequent preferences visualization are carried out in AFRYCA 2.0,[14] an analytic framework able to carry out analyses and studies for GDM problems.

Let us suppose a group of renowned PhD $E = \{e_1, e_2, e_3, e_4, e_5, e_6, e_7\}$ that have to select the best conference in 2018 on Data Science and Knowledge Engineering among four possible alternatives $X = \{a_1, a_2, a_3, a_4\}$. The experts provide their preferences by using FPR, having been available the data set for public access in AFRYCA website[a].

The evolution of the experts' preferences across the CRP are graphically represented in Fig. 1. Notice, the experts' preferences are represented with respect to the collective opinion thus, it is always represented in the center of the picture of each discussion round. The graphical information provided by the proposal facilitates the analysis of relevant aspects and difficulties found in GDM problems, such as conflicting opinions between experts, non-cooperative behaviours or disagreeing experts. In this example, it is easy to detect that the experts are receptive to the suggestions and no expert presents a non-cooperative behaviour, favouring the agreement between experts.

[a] http://sinbad2.ujaen.es/afryca/

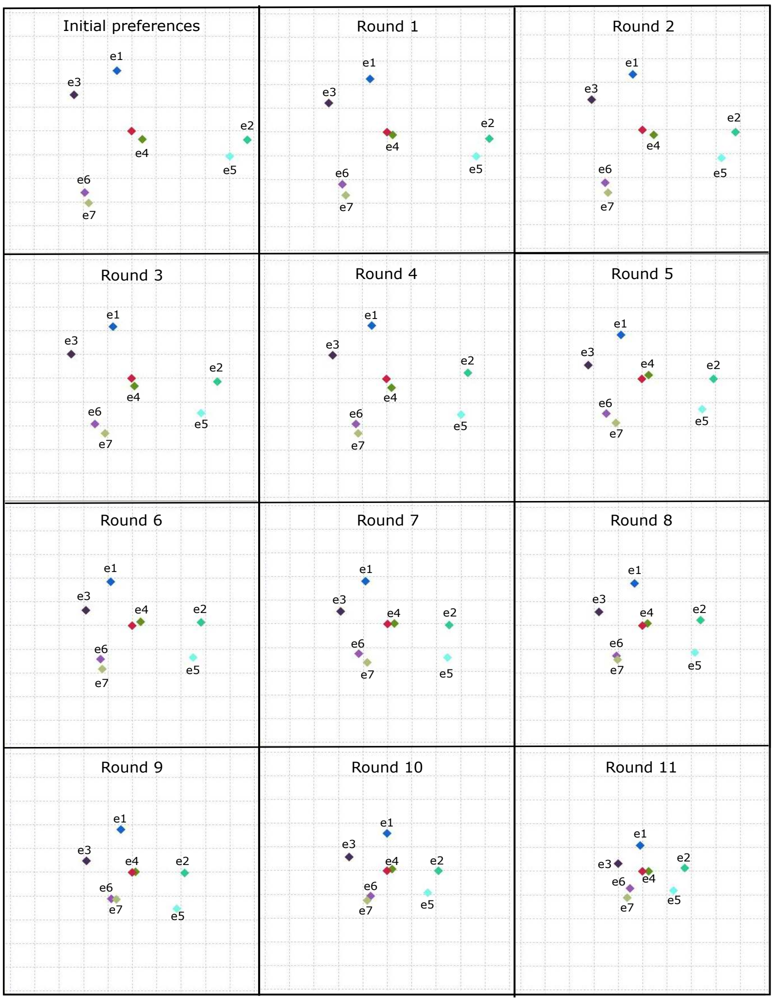

Fig. 1. CRP experts' preferences evolution

5. Conclusions

Experts' preferences visualization in GDM is tremendously useful when a CRP is applied, since it allows to identify easily the experts' behaviour and evaluate the CRP performance. A novel visualization technique has been introduced in this contribution. The proposal is able to deal with multiple preference relations, reducing its dimensionality using the PCA technique and representing the experts' preferences in a bidimensional map.

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