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Open source tool in R language to estimate the inference of the Fuzzy Cognitive Map in environmental decision making

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Abstract: Fuzzy cognitive maps (FCMs) have gained popularity within the scientific community due to their capabilities in modelling and decision making for complex problems. However, despite the large number of papers presenting advances in mathematical formulation and applications of FCMs, along with some recent tools for this soft computing technique, there is a lack of open source tools with sufficient flexibility for modelling and inference in diverse application domains. Filling this gap, this paper presents an open source package in R programming language, called the 'fcm' package, which is able to do scenario analyses and to examine and estimate the inference of FCM, using the `fcm.infer` function. Six different inference rules (kosko, modified-kosko, rescale rule, and the clamped versions of these rules) and four threshold functions (bivalent, trivalent, sigmoid and hyperbolic tangent) are provided. This open-source package is available in CRAN and is relatively easy to use, even for less experienced users. It thus provides the opportunity for researchers in different fields to analyse their weighted matrices as FCM. This paper shows examples and visualizations to demonstrate the proposed open source FCM package for environmental modelling and decision making.

Keywords: Fuzzy Cognitive Maps; fcm package; R programming language; environmental decision making.

1 INTRODUCTION

A Fuzzy Cognitive Map represents expert knowledge about a system graphically, as a directed weight map. It consists of concepts, where each concept represents an element of the system. These concepts are connected to each other using directed edges, which express cause-and-effect relationships among concepts. The method was first proposed by Kosko (1986) for modelling and understanding systems

with numerous interconnections between important components. FCMs integrate properties of fuzzy logic and neural networks, namely the ability to represent the structured knowledge of the system and to compute the inference using a numeric matrix operation instead of simple IF-THEN rules, which require that rule hierarchies are determined (Kosko, 1992).

In recent years, FCMs have been applied in many scientific areas such as: social and political sciences, engineering, information technology, robotics, expert systems, medicine, education, prediction, and business (Papageorgiou and Salmeron, 2013). In ecological and environmental management, the FCMs have been applied in different problems where the structures of the FCMs were based on expert or stakeholder knowledge. Many researchers as referred to by Papageorgiou and Kontogianni (2012), followed the pioneering work of Özesmi and Özesmi (2001), who proposed a multi-step FCM approach to analyse the responses of several stakeholders groups. FCMs have been employed in a number of studies, such as the following: an FCM for cotton yield management in precision agriculture (Papageorgiou et al, 2010), an FCM for describing system dynamics as land cover in the Brazilian Amazon (Soler et al, 2012) and evaluating the future water in the Seyhan Basin (Cakmak et al, 2013), a FCM for analysing scenarios regarding a bio-based economy in the Humber Region (Penn et al, 2013), an FCM for assessing coastal stakeholders knowledge of climate vulnerability in Ireland and Scotland (Gray et al, 2014), an FCM for improving agricultural policy design by analysing the views on regulation between farmers and non-farmers (Gray et al, 2015). Furthermore, FCM models have been used to analyse change, preferred states and perceived resilience of social-ecological systems (Christen et al, 2015), to provide a shared conceptual model among stakeholders to support integrated ecosystem assessments (using social and ecological concepts) (Vasslides et al, 2016), and to assess perceptions about river management s of the Esla River basin in Spain (Solana-Gutiérrez et al, 2017). Many of these applications rely on custom-made software solutions that are only available to the authors, making it difficult to reproduce findings. Furthermore, most studies use very limited inference approaches without comparing results for different computational choices.

The aim of this paper is to provide researchers and practitioners with a flexible tool for FCM modelling with advanced analysis capabilities that can support decision making and policy analysis in a range of studies. To this end, we have developed the 'fcm' package in R language (Dikopoulou and Papageorgiou, 2017b). R is a powerful language and environment for statistical and graphical techniques. Its main advantages lie in the fact that R is available as a free software and it provides a lot of online help. The fundamental "fcm" package provides users a selection of 6 different inference rules (the main three are: Kosko, modified-Kosko, rescale and the clamping versions which are: clamped-Kosko, clamped-modified-Kosko, clamped-rescale) and 4 threshold functions (bivalent, trivalent, sigmoid and hyperbolic tangent) in order to obtain the FCM inference (Kosko, 1986, 1994). The clamping types of these rules are determined when the activated concepts (concept's value equals to 1) are activated in all states during the FCM simulation, until the output is stabilized. Step-by-step instructions on how to use 'fcm' package are provided to acquire the FCM inference of the system. We illustrate this process with an ecological modelling problem that is one of the first uses of FCM in ecological modelling, namely Özesmi and Özesmi (2001).

The rest of the paper is organized as follows: the next Section introduces the foundations of FCM methodology. Section 3 includes the introduction and the use of the "fcm" package and the results of the fcm.infer function are displayed in Section 4. Useful information about the fcm.infer function and further recommendation for users of the fcm package are described in Section 5 and Section 6, respectively. Finally,. Section 7 outlines the conclusions.

2. FUZZY COGNITIVE MAPS (FCMs)

FCM originated from graph theory. The first graph theory was formulated by Euler in 1736 (Biggs, 1976). In 1965, the theory of directed graphs (digraphs) for studying structures of empirical world was presented by Harary (1965). Some years later, Axelrod (1976) introduced cognitive maps for representing social scientific knowledge, derived from humans, to determine the graphical casual relationships between variables. Later, Kosko (1986) extended the methodology of cognitive maps to fuzzy cognitive maps considering fuzzy values for the concepts and fuzzy degrees among concepts. Consequently, a FCM depicts the whole system as a graph, consisted of concepts that reflect attributes, characteristics and qualities of the system and weighted directed edges that determine the causal-effect influences between the concepts, as well.

The cause and effect interconnection between two nodes C_i and C_j is described with the weight w_{ij} , with w_{ij} taking value in the range -1 to 1. There are three possible types of causal relationships between concepts:

- $w_{ij} > 0$ indicates positive causality between concepts C_i and C_j . That is, an increase (decrease) on the value of C_i leads to an increase (decrease) on the value of C_j .
- $w_{ij} < 0$ indicates negative causality between concepts C_i and C_j . That is, an increase (decrease) on the value of C_i leads to a decrease (increase) on the value of C_j .
- $w_{ij} = 0$ indicates no relationship between C_i and C_j .

Once the FCM is constructed, it obtains data from its input concepts, performs reasoning and infers decisions according to the concepts' output values (Papageorgiou & Stylios, 2008). During reasoning, the FCM repeatedly determines the concepts' states until convergence. The inference process is implemented for the simulations performed for making policy decisions (scenarios). In accordance with the interests of the decision maker, simulation can be accomplished with either all concepts or a subset of concepts being activated. Mathematically a FCM of n concepts could be represented by a n state vector (A) which gathers the values of the concepts and by a $n \times n$ weight matrix (W). Having assigned values A_i to the concepts C_i and weight among concepts, the FCM converges to an equilibrium point using one of the following calculation rules, Eq.(1)-(3):

Kosko:
$$A_i^{(\kappa+1)} = f\left(\sum_{j=1, j \neq i}^n w_{ji} \times A_j^\kappa\right) \quad (1)$$

Modified-kosko:
$$A_i^{(\kappa+1)} = f\left(A_i^\kappa + \sum_{j=1, j \neq i}^n w_{ji} \times A_j^\kappa\right) \quad (2)$$

Rescale:
$$A_i^{(\kappa+1)} = f\left((2 \times A_i^\kappa - 1) + \sum_{j=1, j \neq i}^n w_{ji} \times (2 \times A_j^\kappa - 1)\right) \quad (3)$$

where $A_i^{(\kappa+1)}$ is the value of concept C_i at simulation step $\kappa + 1$, $A_j^{(\kappa)}$ is the value of concept C_j at the simulation step κ , w_{ij} is the weight of the interconnection between concept C_i and concept C_j , κ (Greek letter Kappa) is the interaction index at every simulation step and $f(\cdot)$ is the threshold (activation) function. The function is selected to retain the values within the range $[0, 1]$ or $[-1, 1]$. Generally, there are four most commonly used transformation functions Eq.(4)-(7): (a) bivalent, (b) trivalent, (c) sigmoid and (d) hyperbolic tangent. In most studies, the sigmoid function is widely applied to obtain the inference of the system (Papageorgiou, 2014).

Bivalent:
$$f(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases} \quad (4)$$

Trivalent:
$$f(x) = \begin{cases} 1, & x > 0 \\ 0, & x = 0 \\ -1, & x < 0 \end{cases} \quad (5)$$

Sigmoid (linear):
$$f(x) = \frac{1}{1 + e^{-\lambda x}} \quad (6)$$

Hyperbolic tangent:
$$f(x) = \tanh(\lambda \times x) \quad (7)$$

where λ is a real positive number ($\lambda > 0$), which determines the steepness of the continuous function f and x is the value $A_i^{(\kappa)}$ on the equilibrium point. The FCM model of the system takes the initial values of concepts and weights based on experts' knowledge and experience for the real system and then it

is free to interact. At each step, the value A_i of a concept is influenced by the values of concepts connected to it and it is updated according to the inference rule. This process continues until the system converges which indicates that the difference between two subsequent values of the outputs must be equal or lower to ε (epsilon, $\varepsilon = 0.001$).

3 APPLYING THE 'fcm' PACKAGE

To illustrate the use of the R package, this section uses an FCM of an ecological problem as described by Özesmi and Özesmi (2001). It is visualized in Figure 1, using the 'fcm' package. The model consists of five concepts, C_1 – Area size of wetlands, C_2 – Fish Population, C_3 – Pollution, C_4 – Livelihood, C_5 – Law Enforcement. There are 11 causal relationships between the concepts, which are shown in Figure 1 along with the corresponding weight matrix (right). In the figure, positive edges are blue and negative edges are red. The thicker and more saturated the edges are, the stronger the relationship between cause and effect, relative to other edges in the map. In the weight matrix, weights are assigned accordingly. We use 'fcm' package to test how the system behaves in response to activating the initial state of the "Law Enforcement" concept ($C_5 = 1$) while all other concepts' values are set to zero ($C_1 = C_2 = C_3 = C_4 = 0$). We demonstrate how to set up the estimation of the inference for this input scenario (Scenario I) for the three calculation rules (Kosko, modified-Kosko and Rescale) and a sigmoid f transformation function as described in Section 2.

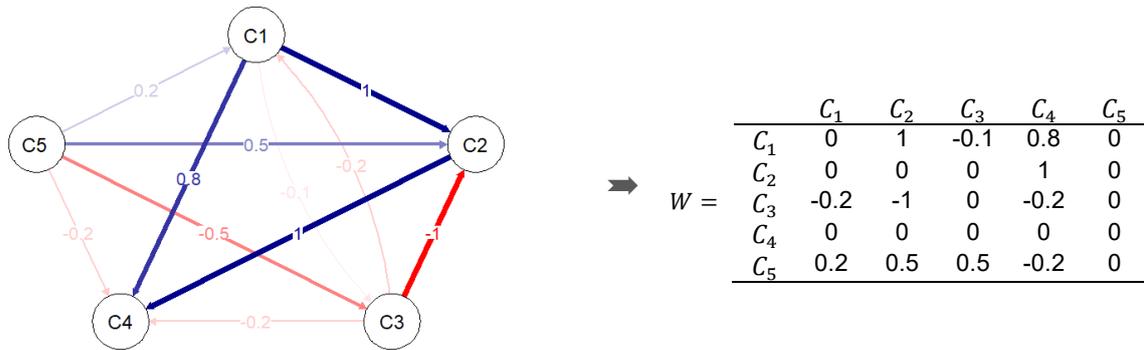


Figure 1. Fuzzy cognitive map (left) and the correspondent weight adjacency matrix (right), showing the positive and negative causal influences

3.1 The FCM inference process in R

We provide step-by-step instructions on how to use 'fcm' package, including its installation, the setup of the model and an initial state vector, the use of **fcm.infer()** to estimate the inference, and the interpretation of the three outputs that are returned by the package: (a) a data frame which contains the concepts' values of each iteration (b) a FCM map (as presented in Figure 1) and (c) the convergence plot of κ steps.

Step 1: Install and load the "fcm" package: The fcm package can be downloaded and installed by running the code: `install.packages("fcm")` only once from the Comprehensive R Archive Network (CRAN) (<http://CRAN.r-project.org>); afterwards, it can be loaded: `library(fcm)`

Step 2: Create the initial activation vector: In R, a single-dimensional vector is created using the `data.frame` function and saved as `A1`:

```
A1 <- data.frame(0, 0, 0, 0, 1).
```

Next the column names of `A1` are inserted: `colnames(A1) <- c("C1", "C2", "C3", "C4", "C5")`

Step 3: Create the weight matrix: The weight matrix in Figure 1 could be created using the matrix function:

```
W <- matrix(c(0, 1, -0.1, 0.8, 0,
              0, 0, 0, 1, 0,
              -0.2, -1, 0, -0.2, 0,
              0, 0, 0, 0, 0,
              0.2, 0.5, -0.5, -0.2, 0), nrow=5, ncol=5, byrow=TRUE)

colnames(W) <- c("C1", "C2", "C3", "C4", "C5 ") # column names in of W
```

Step 4: Apply the *fcm.infer* function: The function **fcm.infer()** is applied for estimating the FCM inference. First, the initial activation vector A_1 is determined according to scenario I to activate the initial state of the concepts, the weighted matrix W should follow. Next, the number of iterations are determined. In order to specify the inference rule, the argument *infer* must be equal to one of the provided inference rules (Kosko: 'k', modified Kosko: 'mk', Rescale: 'r', Kosko-clamped: 'kc', modified Kosko-clamped: 'mkc' or Rescale-clamped: 'rc'). After that, the transformation function (*transform*) is specified. Four transformation functions are available (Bivalent: 'b', Trivalent: 'tr', Sigmoid: 's' or Hyperbolic tangent: 't'). Finally, parameter λ (λ) is determined as a positive number, higher than zero and lower-equal to ten, $0 < \lambda \leq 10$ and the possible residual value ε (epsilon) is defined between 0.01 and 0.000001. In case that values of λ and ε are not be defined in the *fcm.infer()* function, the default values for λ (λ) is 1 and for ε (ε , epsilon) is 0.001.

For the estimation of the FCM inference regarding the Scenario I, three different lines of coding in R are typed. The inference rules are modified into 'k' for Kosko rule, 'mk' for modified-Kosko and 'r' for Rescale rule, Eq. (1) – (3). The activation vector (A_1), the weight matrix (W), the number of iterations ($iter = 20$), the transform function (Sigmoid 's'), $\lambda = 1$ and $\varepsilon = 0.001$ remain the same:

```
fcm.infer(A1, W, 20, 'k', 's', lambda = 1, e = 0.001) # Kosko
fcm.infer(A1, W, 20, 'mk', 's', lambda = 1, e = 0.001) # modified-Kosko
fcm.infer(A1, W, 20, 'r', 's', lambda = 1, e = 0.001) # Rescale
```

The 'fcm' package imports three additional packages: *qgraph*, *reshape*, *ggplot2* which are useful for creating graphs and plots. This means that after the inference estimation, the *fcm.infer* function returns not only a data frame which contains the concepts values of each iteration but also graphical objects, such as: the FCM map and the convergence plot of κ steps.

4. RESULTS OF THE 'fcm' PACKAGE

In this section, the results of *fcm.infer* function, applied in Scenario I, are presented. It is important to mention that the *fcm.infer* function stops when the equilibrium point is converged. Moreover, the converged values of all κ steps appear in the R-console and the convergence plot in the R-plot pane. Specifically, Figure 2 displays the environment of RStudio and the obtaining results from the Scenario I. In the console pane (down-left), the converged values of the vector A_1 are shown. As it is observed, the iterations stopped at the 7th step and the converged vector (final state) is $A_1^7 = [0.663 \ 0.7753 \ 0.5342 \ 0.8750 \ 0.6590]$. Furthermore, the plot pane (down-right) demonstrates graphically the convergent values of the console pane. The explanation of the simulation is simple. Scenario I examines the impact of "Law Enforcement" to the remaining concepts of the system. In other words, the policy option that Scenario I holds, must answer the question "if the law enforcement increases ($C_5 = 1$) what will be the effect to the observed concepts of the FCM?". The activation levels at the final vector and changes/trends in the activation levels throughout the simulation (Figure 2) indicate that increasing the enforcement of laws, the livelihoods of the people living around the Kizilirmak Delta area (C_4) increase significantly. Furthermore, fish population (C_2) and the wetlands (C_1) increase; while, the environmental problem in this system, pollution (C_3), increases but not considerably.

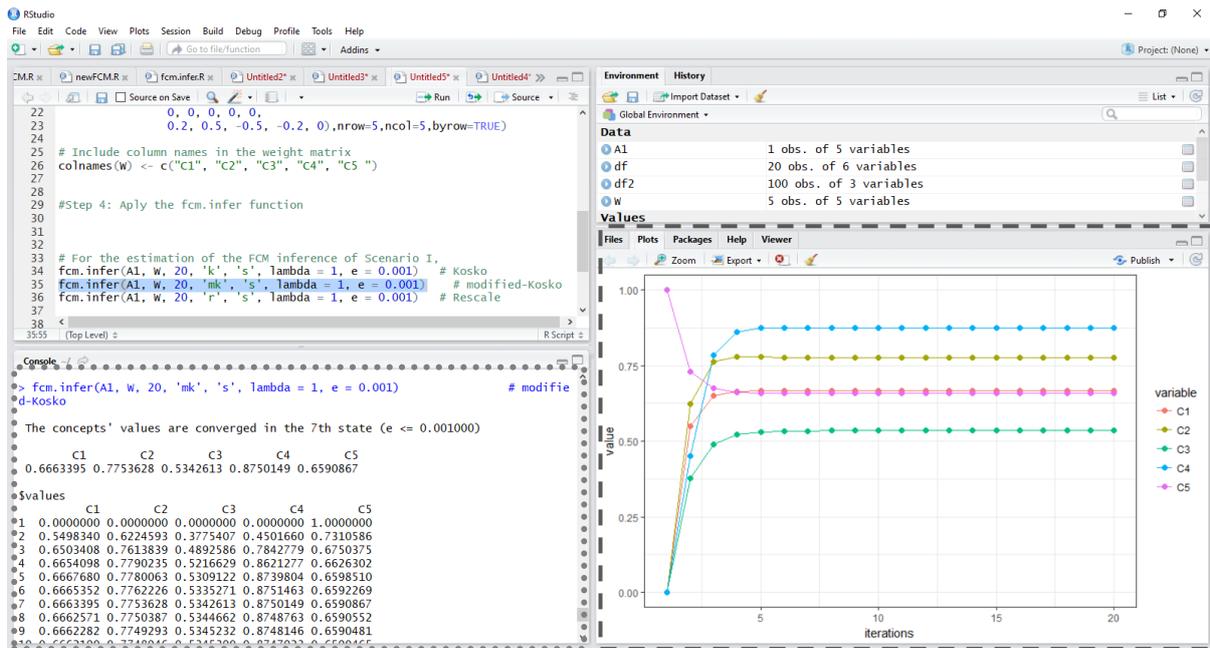


Figure 2. RStudio environment. The results of a `fcm.infer` function are presented in Console pane and Plot pane (results are for modified Kosko inference).

5 SUMMARY OF RESULTS AND DISCUSSION

The goal of this paper is to teach the users how to use the 'fcm' package as simple as possible to infer their decision policies on their own FCMs. The user needs to specify the activation vector and the weighted matrix. Therefore, the `fcm.infer()` function is used to accomplish the FCM simulation which includes the arguments (initial activation vector, weighted matrix, number of iterations, inference rule, transformation function, lambda value and epsilon value) as input to the function, within the parentheses (). Afterwards, the `fcm.infer` function informs the user that the equilibrium point (convergence) of the system has been reached in the *i*th activation state (step or iteration). For example, in console pane (Figure 2) is depicted a message "The concepts' values are converged in the 7th state (e <= 0.001000)" which notifies that the equilibrium point is completed at the 7th state. Hence, the `fcm.infer` function returns a data frame including the activation values of the concepts of each iteration. Finally, the `fcm.infer` function imports the `ggplot2` function to turn the concepts' values of each iteration into a useful visualization plot (Figure 2 (plot pane)). On this plot, x-axis and y-axis include the number of iterations and the values of the concepts, respectively.

While using the package requires a basic understanding of R, it does not require programming skills or lengthy set ups: A single line of code represents all relevant modelling choices and instantaneously results in data frames and visualizations. This gives FCM modellers a lot of flexibility in how they set up their project and allows them to quickly compare the outcomes, given their different modelling choices (e.g. alternative transfer functions or inferences). This is likely to benefit FCM research in multiple ways: First, it provides more transparency: FCM publications often fail to fully describe all modelling choices and current FCM tools (e.g. www.mentalmodeler.org) are black boxes, giving end user limited options for determining the exact inference mechanism and transfer function. As researchers adopt the proposed package, their approaches will become more transparent and reproducible. Also, the option to quickly compare results of alternative modelling decision (e.g. the choice of transfer functions with different slopes) may invite FCM practitioners to more rigorously test their models and justify their decisions. And finally, because of the modular and open nature of R programming, it is easy to integrate the package in different projects or modify it. Our own future efforts are focused on designing and developing new packages in R for FCM learning algorithms and other optimization methods. Other researchers may want to use the package as the backbone for improved FCM visualization techniques or for implementing exploratory modeling strategies. We therefore expect that the package can become a platform for methodological innovations in FCM research.

6 RECOMMENDATIONS TO USERS

In order to use the current version of the 'fcm' package (version 0.1.3), it is necessary to install it as described in sub-section 3.1. Assure that have a recent version of R (at least version 3.3.2) from <https://cran.r-project.org/>. Moreover, it is important to download the latest version of the package you are interested in because bugs have been solved or some extensions have been added. For reporting bugs in 'fcm' package, please submit them in <https://github.com/LiaDD/Fuzzy-Cognitive-Maps-FCMs>.

Concerning the visualizations, every user can modify the colors of the plot according to the suggestions of ggplot2 package which is not the subject of this paper work. 'fcm' package includes the standard palette of colors of the ggplot2 as depicted in Figure 2.

Furthermore, if the number of concepts is increasing, the execution time of the algorithm is increasing likewise. In other words the R code will run slower comparing to other coding programming languages (such as Python, C++, etc) but it will deliver the appropriate results. According to Wickham (2014), a Chief Scientist at RStudio "*R is not a fast language. This is not an accident. R was purposely designed to make data analysis and statistics easier for you to do. It was not designed to make life easier for your computer. While R is slow compared to other programming languages, for most purposes, it's fast enough*".

7 CONCLUSIONS

In this study, an open source R package, "fcm", available in CRAN (<https://cran.r-project.org/>) is introduced and illustrated with a case from the literature. The package can retrieve the inference of any FCM, offering a variety of simulation options and different parameters. Particularly, six inference rules, six threshold functions and a range of values for λ and ε parameters are supported. The algorithm of the fcm.infer function stops when the equilibrium point for each concept is reached. The values of each concept of each iteration are presented as well as the correspondent graphical plot. The fcm.infer() was applied in an ecology system in order to show the capability and the flexibility of this package in R which only one line of code is required to reach the convergence of the system.

The provided package in R can be used by diverse users with only basic R skills, including experts, stakeholders, and policy analysts create FCM models and build simulations for different scenarios. The "fcm" package was designed to be user-friendly and reusable, and has the potential to facilitate method innovations.

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