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Fuzzy cognitive maps: a tool to improve diagnostic decisions

Abstract: Anticipating that the problem of diagnostic errors will not easily be solved through education, debiasing techniques or incentives-based systems, experts have proposed the systematic use of decision support tools (or decision aids) in medical practice. These tools are active knowledge resources that use patient data to generate case-specific advice to support clinical decision making. We argue that designing these decision support tools incorporates both discrete, analytical information as well as intuitive elements that would optimize their impact on clinical everyday activities. The use of fuzzy cognitive maps should allow developers to achieve this aim, by incorporating published evidence, intuition and qualitative assessment in a low-cost software program that could be implemented in various clinical settings.

Keywords: decision support systems; diagnostic errors; dual process theory; fuzzy cognitive maps.

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Problems in diagnostic decision

The diagnostic process is one of the main focuses of medical decision making. Indeed, establishing a diagnosis is a complex task: A physician is expected to act as an information processor, able to both collect information and process it efficiently to produce hypothesis about the clinical case and further examinations needed to evaluate them. We could describe the diagnostic process using a simple scheme (see Figure 1).

Substantial research has been devoted to this important topic, but relatively little is known about the exact mechanisms of the diagnostic process, both when it succeeds or fails. Indeed, diagnostic errors account for a substantial number of all medical errors and even though it has recently received increasing attention [2, 3] it remains an important patient safety concern [4, 5].

Given the complexity of the diagnostic process, experts have proposed that the systematic use of decision support tools (or decision aids) in everyday clinical practice could improve diagnostic reliability and reduce the likelihood of error.

A decision support system (DSS) is an active knowledge resource that uses patient data to generate case-specific advice, which supports decision making by health professionals, the patients themselves or others concerned about them [6].

A cognitive balanced model (CBM)

Several authors have described how experts typically employ subconscious, intuitive, synthetic thinking (System 1, S1) [7, 8]. In contrast, others have argued that physicians should adopt exclusively analytical approaches to problem-solving, which would be less prone to intuitive bias and emotional contamination. In this case, a good doctor would be a pure rational decision maker, able to follow precisely step-by-step algorithms. If errors should arise in this setting, it would indicate the intrusion of heuristics and/or wrong procedures due to a poor professional training, or to contingencies, such as a negative mood, excessive stress, or distractions like a noisy environment. Most DSSs are based on the idea that physicians need help in enhancing their analytical thinking, encouraging users to abandon intuition in favor of procedural reasoning. Unfortunately, this conceptual architecture limits the actual use of DSSs, because most

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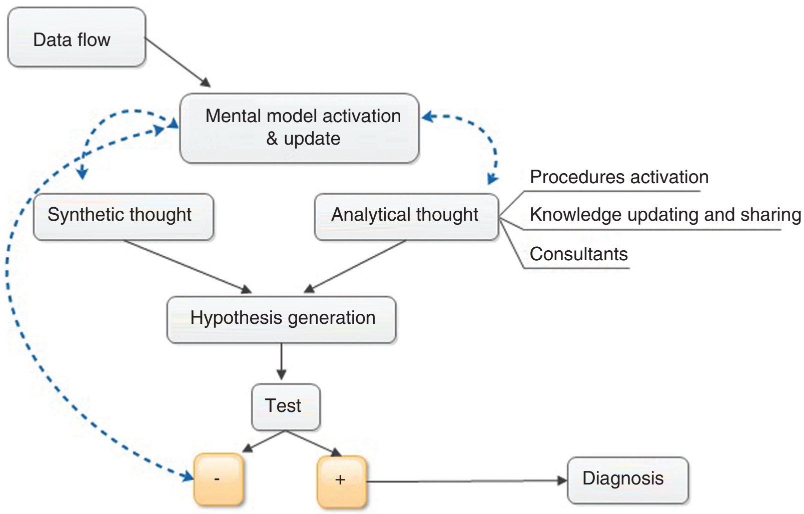

Figure 1 Mental model is the physician's cognitive structure that incorporates and gives sense to the data flow coming from the environment (patients' symptoms, clinical tests and the like).
From this mental structure both analytical and synthetic thinking may be activated in order to generate and evaluate hypotheses. We use the term synthetic thinking to indicate all those processes that do not require conscious data decomposition and representation. This kind of thinking is generally defined as intuitive or heuristic [1].

physicians, especially expert and skilled ones often rely on, intuitive thinking, their "clinical-eye".

However, others have pointed out the valuable role of intuition in making good medical decisions [9, 10]. For instance, Gabbay and Le May [11], described how expert physicians develop strategies based on the use of subtle clues to quickly infer important judgments without a complete information base. They called these strategies "mindlines" as opposed to guidelines.

In previous works [12, 13], we have defined a cognitive balanced model (CBM) to describe how clinical decisions should emerge from a functional balance between analysis and intuition, guidelines and mindlines. The CBM underlines the need for a doctor to develop both intuitive and analytical skills, and the potential benefit of using a decision support system that enables physicians to find the balance needed case by case, adapting the thinking style to fit the actual demands of the problem. Medical practitioners must learn to trust their intuition, but also know how to prevent heuristic-related fatal biases.

Fuzzy cognitive maps

The need to accommodate this dynamic balance and the natural presence of uncertainty in most clinical settings requires a decision support resource capable of handling this complexity, such as one based on fuzzy cognitive maps (FCM) [14].

To build a FCM, doctors are not required to quantify the importance of contributing information, they only need an intuitive comprehension of a clinical scenario, and the relevant factors that need to be considered. As shown in different experimental studies, FCM can improve the diagnostic process by incorporating a cognitive balanced decision [15, 16]. The great advantage of this approach is that it provides the possibility to incorporate heuristics and intuitive knowledge in a defined conceptual scheme [17]. This includes both analytical (S2) and synthetic components (S1), often described as divergent concepts in a decision process but perfectly integrated in the FCM balanced model.

A formal model for clinical settings

As described before, a FCM is a graph modeling a dynamic, complex system, consisting of nodes (C_i) and interconnection (e_{ij}) between concepts, expressing cause and effect relations between them.

The general formula expressing the value of each concept C_i is the following, in which the value of each concept C_i is calculated computing the influence of other concepts to the specific one, through the calculation rule given by the equation:

$$x_i(t)=f\left(\sum_{\substack{j=1\\ j\neq i}}^{n} x_j(t-1)w_{ji}\right) \quad (1)$$

where $x_i(t)$ is the value of the concept C_i at time t; $x_j(t–1)$ represents the value of the concept C_j at time t–1; w_{ji} is the weight of the interconnection between C_j and C_i; f represents the sigmoid function

$$f=\frac{1}{1+e^{-\lambda x}}$$

The weights w_{ji} characterize the interconnections. They describe the degree of causality between two concepts and can assume values in the interval [–1, 1]. The sign of a weight respectively indicates positive causality that is an increase in the value of the concept C_i will cause an increase in the value of the concept C_j, or negative causality. In this latter case the increase of the value of the concept C_i will cause the decrease in the value of C_j or the decrease of C_i will cause the increase of C_j. If the weight is equal to zero, there is no relationship between the two concepts. In summary, the strength of the weight w_{ji} reflects the degree of influence between concept C_i and C_j.

To model the mutual and reciprocal influence of S1 and S2 (intuitive and analytical thinking), these relationships are described by the equations 1 and 2 (1) introducing a modification of the weight w_{ji} as follows. A panel of experts is asked to consider all of the individual concepts, attributes, interconnections and relative weights, representing the graphical display of a given clinical scenario (a connected graph). The experts are then asked to express two parameters: one formulated on the basis of their experiences and intuitions (S1), the other deriving from objective data and evidence-based analysis (S2). The new weights w'_{ji} in the formulas (1) and (2) will be so obtained by the sum of the weights indicated by the experts, namely S1 and S2, corresponding to the two thinking systems:

$$w'_{ji}=\mathrm{S1}+\mathrm{S2}$$

The formulas will be:

$$x_i(t)=f\left(\sum\nolimits_{\substack{j=1\\ j\neq i}}^{n} x_j(t-1)w'_{ji}\right) \tag{1b}$$

$$x_i(t)=f\left[k_1\sum\nolimits_{\substack{j=1\\ j\neq i}}^{n} x_j(t-1)w'_{ji}+k_2x_i(t-1)\right] \tag{2b}$$

where w'_{ji}=S1+S2

We chose the sum because it is the simplest calculation and it preserves the meaning of the weights in the formulas, both in the regard to direction (positive or negative influence) and magnitude.

The different FCM resulting from the work of the panel of experts will be evaluated by an automatic system comparing the results with the expected ones. We are not able to predict a priori which of the two formulations will optimally converge, so we argue that both the presented FCM mathematical formulations need to be tested.

An example

To illustrate how our model works, we propose here a simplified, though realistic, model of a differential diagnosis between psychogenic non-epileptic (PNES) and epileptic seizures (ES) [18]. The differentiation of the two pathological conditions is often not trivial, since the symptomatology of both ES and PNES is particularly variable, the behavioral features of PNES can simulate epileptic ones, and both types of seizures may occur in the same patients. The complexity of this problem fits our aim, because FCMs are particularly useful in ambiguous contexts and when incomplete or not completely reliable information must be used. Figure 2 presents a simplified model of the problem: Clouds indicate decision-concepts, that is the two diagnoses we are considering; ellipses describe the most important factors (factor-concepts) involved in distinguishing the two possibilities, the input of our FCM.

The following characteristics should be considered to differentiate ES and PNES in ambiguous cases: Anamnestic information (history of neurological and psychiatric disorders, in particular the presence of significant psychological trauma), clinical data (the presence of brain pathology, a mood disorder, a neurological condition, EEG abnormalities, and hormonal indices, e.g., post-ictal serum level of prolactin), behavioral features (response to antiepileptic drugs and/or placebo, provocation of seizures, typicality of symptoms), psychological/psychiatric aspects (assessment of personality) and demographic data (e.g., PNES is more common in women). All this information should be integrated to suggest a final conclusion [18, 19] because any single information source, might, almost equally, suggest either ES and PNES. Furthermore, some of these data are difficult to collect, being not always available or reliable.

Following the simpler FCM model proposed by Georgopoulos and Stylios [20] we could use the clinical data alone to obtain a fuzzy-based decision aid. However, we argue that the utility of the FCM would be strengthened by incorporating both analytical and intuitive input. To illustrate this process, we asked an expert neurologist to consider the differentiation of ES from PNES based on his expertise. The analytical and the intuitive differentiation model obtained are the results of two different information sources. The former is evidence-based and it should be assembled by an independent expert (or panel of

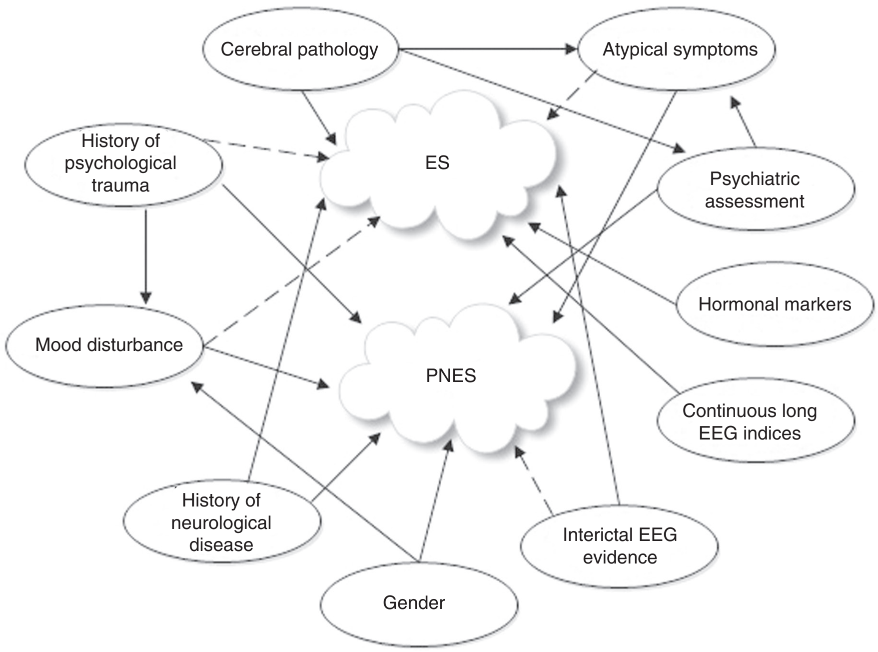

Figure 2 A simplified model of the ES/PNES differentiation problem.
Dashed lines indicate weak or uncertain connections. Clouds represent decision-concepts, and ellipses represent factor-concepts. Factor-factor connections may be either positive (synergic) or negative (competitive).

experts) asked to consider only dedicated literature. This generally (but not always) implies the construction of a complex model where many factors and interactions are considered. In cases where the evidence is strong and clearly stated, this model should be the optimal one. The second differentiation model is instead expertise-based, and is generally simpler, since the actual experience of the doctor guides the weighting process. Those factors previously found to efficiently discern ES and PNES in concrete occurrences, despite strong scientific evidence, should be, for example, overweighted.

Finally, we carried out a balanced weighting procedure of each attribute, based both on literature data (S2) and the doctor's expertise (S1; see Table 1). The values can be summed to incorporate the final weight of a simple syntax, we then summed the two values obtaining the final weight of each attribute in the FCM software. In this way, the ultimate output reflects both analytical and synthetic considerations.

This Table is used to populate the FCM model, determining the relative importance of each of the m factor-concepts with respect to the n possible (2 in our example) decision-concepts. These fuzzy weights will be translated into numerical weights by the algorithm used. For instance, very high corresponds to 90% of relevance of a given factor and the weight assigned will be 0.9.

Table 1 Weights attributed by the use of analytical and synthetic thinking to decision attributes of the FCM.

Attributes	Synthetic weight (S1)		Analytical weight (S2)	
	PNES	ES	PNES	ES
Presence of cerebral pathology	Low	Medium	Medium	High
Gender (women)	Low	Low	Medium	Low
Interictal EEG alteration	Medium	High	0	High
Long-term EEG monitoring	Low	High	0	High
Hormonal indices	Low	High	0	High
History of psychological trauma	High	Medium	High	0
Psychiatric assessment	High	Medium	High	Low
History of neurological diseases	Medium	High	Low	High
Mood disturbance	High	Medium	High	Low
Bizarreness of symptoms	High	Medium	High	Low

To sum related weights we used the following simple rules (S1+S2): 0 + any Value = 0; Low+Low = Low; Low+Medium = Medium; High+Low = High; Very high + Low = Medium; Medium + Medium = Medium; Medium + High = High; Medium+Very High = High; High + High = High; Very High + Very High= Very High. In this case, we decided to give equal weights to S1 and S2, but in a given situation different weights should be assigned. Actually, these assignments should be regarded as arbitrary and could be modified to fit specific clinical contexts and/or to the confidence a doctor has with expertise-based or evidence-based models. This means that clinicians deciding to use this decision support tool could adapt it to his/her decision style by appropriate adjustments to the weighting rules.

Consequently the FCM algorithm will work on two matrices, W and X. Matrix W contains all the connection weights, and may include negative values if competitive connections between factors are present, while X contains the values assigned in a specific case. To place values in X, the decision maker will assign values to each attribute present in the FCM-model, using the same fuzzy degrees (0, low, medium, high or very high). Naturally, only data actually available will be placed in X, while the input-factor not available will correspond to nodes not activated (0 values). For instance, in a specific case, a doctor could use the FCM decision aid using only EEG signal abnormalities, the history of neurological disorders and the presence of mood disturbance, assigning respectively High, Medium and Low as fuzzy degrees and 0 to all other model factors (in this case the model would suggest a diagnosis of ES).

Conclusions

We argue that fuzzy cognitive maps, already recognized and tested in the domain of medical diagnosis, have received inadequate attention by researchers and doctors. It is likely that in the near future more FCM-based decision aids will become available both during medical training and in everyday clinical practice, providing a better balance of analytical and synthetic mental processes with beneficial effects on decision making and patients' outcomes. The FCM approach provides a method to handle uncertainty in clinical decision-making when uncertainty is expected to be high. The fuzziness of the maps allows one to visualize the hazy degrees of causality between concepts, and their graphic structure allows easy visualization of the relationship between concepts.

Furthermore, we argue that training doctors to balance intuitive and analytical thinking will enable them to increase their cognitive awareness about how they reason, decide and solve problems and sensitize them the consequences of medical decisions, both and negative. In this way, doctors will strengthen their ability to learn from practice, developing a easily adaptable expertise, particularly useful in situations of high complexity or rapid evolving evidence.

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