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Fuzzy Cognitive Maps for Analyzing User Satisfaction in Information Services

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ABSTRACT
In this paper, we develop a Fuzzy Cognitive Map (FCM)-based framework for investigating user satisfaction in information services and further focus on how various affecting factors are connected to the overall user service experience. Conventional approaches usually perform poorly with extensive uncertainties or difficult, complex relationships between service quality, response time, usability and personalization. As a case in point, FCMs give us an appropriate mathematical framework to model causal relationships and simulate dynamic interplays between these factors.
In the study, critical factors are taken as nodes in FCM and then it establishes causal weights between these so that their importance can be quantified. The state of every concept is then updated via matrix-vector operation and iterative updates with sigmoid activation function until convergence. A comprehensive case study illustrates an actual usage of the FCM framework, and highlights its ability to isolate key drivers that impact satisfaction and suggests avenues for improvement.
Next steps include integrating IoT sensors for real-time monitoring, hybrid models with machine learning to improve predictions and relevant applications in different fields which goes from e-commerce to healthcare. This experimentation underscores FCMs potential in decision-making procedures which presents good insight towards enhancing users experience when dealing with information service.
Keywords: Fuzzy Cognitive Maps (FCMs), Information Services, User Satisfaction, Sigmoid Activation Function, Response Time, State Vector Convergence, Hybrid Models, IoT Integration, Decision-Making Framework.

1. Introduction

1.1 Overview of Information Services

Information services including libraries, digital platforms and knowledge systems are vital in the provision of relevant up to date information for end users. Customer satisfaction Grossly, customer satisfaction is one of the major yardsticks for determining the quality as well as responsiveness and relevance of these services (Parasuraman et al., 1988) [4]. Unfortunately, the assessment of user satisfaction is difficult because it involves judging absolutely subjective feedback from customers and interactions that are interrelated among several service factors (Zadeh 1965) [11]. These, for example include factors such as response time; service quality; platform usability and personalization, which are likely to interact significantly with user satisfaction in various multitude of ways. Assuming that these may have non-linear relationships and even wild-card functional forms [3].

1.2 Motivation for Using Fuzzy Cognitive Maps (FCMs)

One of the effective approaches for modelling complex systems with multiple interacting variables is Fuzzy Cognitive Maps (FCMs). Based on cognitive maps of the FCM paradigm (Kosko, 1986) [1,2], but adding another function that is not in standardized cognitive models: fuzziness; to be able to handle environments where uncertainty and partial truths are pervasive. For information services, FCMs is an instrument that helps us to represent how the user satisfaction will depend on several generic factors and modelling quantitatively their cause-effect relationship.

1.3 Objectives and Scope

This study aims to develop an FCM-based framework to assess and analyse user satisfaction in information services. The objectives include as given below:

- Modelling key factors influencing user satisfaction as concepts in an FCM.
- Quantifying causal relationships between these factors using fuzzy weights.
- Simulating dynamic interactions to predict user satisfaction levels.
- Providing actionable insights for improving service quality.

2. Mathematical Foundations of Fuzzy Cognitive Maps (FCMs)

The FCMs are directed graphs in which nodes correspond to concepts (factors of user satisfaction) and the links data-informed causal relationships between pairs of these such combinations. The strength of these relationships is quantified by the fuzzy weights, which enable mathematically modelling complex dynamical cause-effect (Kosko 1986) [2].

2.1 Definition of Fuzzy Cognitive Maps (FCMs)

An FCM is formally represented as a triple $FCM = (C, E, W)$, where:

- $C = \{C_1, C_2, \dots, C_n\}$ is the set of concepts (factors such as service quality, usability, etc.).
- E is the set of directed edges representing relationships between concepts.
- W is the weight matrix representing the strength and direction of causal relationships, where:

$$W = \{w_{ij} \mid w_{ij} \in [-1,1]\}$$

Each w_{ij} denotes the weight of the relationship from concept C_i to C_j.

2.2 State Vector and Weight Matrix

The state vector $A^{(t)}$ at time t contains the activation values of all concepts (i.e., their current levels):

$$A^{(t)} = \begin{bmatrix} a_1^{(t)} & a_2^{(t)} & \dots & a_n^{(t)} \end{bmatrix}$$

where $a_i^{(t)} \in [0,1]$ represents the activation value (or satisfaction level) of concept C_i at time t. The weight matrix W captures the strength of the influence between concepts:

$$W = \begin{bmatrix} 0 & w_{12} & w_{13} \\ w_{21} & 0 & w_{23} \\ w_{31} & w_{32} & 0 \end{bmatrix}$$

Here, $w_{ij} > 0$ indicates a positive influence, $w_{ij} < 0$ indicates a negative influence, and $w_{ij} = 0$ means no direct relationship between concepts C_i and C_j.

2.3 Fuzzy Inference and State Update Equations

The activation values of the concepts evolve dynamically through iterative updates [5]. The state update equation for the FCM is given by:

$$A^{(t+1)} = f\left(A^{(t)} \cdot W\right)$$

where:

- $A^{(t)}$ is the state vector at time t.
- W is the weight matrix.
- $f(x) = \frac{1}{1+e^{-x}}$ is a sigmoid activation function used to keep the concept values in the range [0,1].

This equation describes how the system evolves over time and activation of concepts propagates. When all base states are converged in the same state vector, it means a system already is finalized and represents final user satisfaction levels.

2.4 Fuzzification of Input Data

To incorporate real-world data, user feedback is first converted into fuzzy sets. For example:

Satisfaction Level:

- Low: $\mu_{\text{Low}}(x) = \max\left(0, \frac{50-x}{20}\right)$
- Medium: $\mu_{\text{Medium}}(x) = \max\left(0, \min\left(\frac{x-30}{20}, \frac{70-x}{20}\right)\right)$

- High: $\mu_{\text{High}}(x) = \max\left(0, \frac{x-50}{20}\right)$

If a user provides a satisfaction score of 60, the membership values are:

$$\mu_{\text{Low}}(60) = 0,\ \mu_{\text{Medium}}(60) = 0.5,\ \mu_{\text{High}}(60) = 0.5$$

These fuzzy values are used as inputs to the FCM model [6].

2.5 Example of Weight-Based Causal Influence Calculation

Consider three concepts:

- C_1 = Service Quality
- C_2 = Response Time
- C_3 = User Satisfaction

The initial state vector is:

$$A^{(0)} = [0.7 \quad 0.5 \quad 0.6]$$

Assume the weight matrix is:

$$W = \begin{bmatrix} 0 & -0.4 & 0.3 \\ 0.2 & 0 & 0.5 \\ 0.1 & -0.3 & 0 \end{bmatrix}$$

The next state vector is computed as:

$$A^{(1)} = f\left(A^{(0)} \cdot W\right)$$

Multiplying the vectors:

$$A^{(0)} \cdot W = [0.7 \quad 0.5 \quad 0.6] \cdot \begin{bmatrix} 0 & -0.4 & 0.3 \\ 0.2 & 0 & 0.5 \\ 0.1 & -0.3 & 0 \end{bmatrix} = [0.17 \quad -0.47 \quad 0.56]$$

Applying the sigmoid function:

$$A^{(1)} = f([0.17 \quad -0.47 \quad 0.56]) = [0.542 \quad 0.384 \quad 0.636]$$

2.6 Interpretation of Results

The updated state vector $A^{(1)}$ indicates the new levels of activation for each concept. In this example:

- Service Quality: 0.542 (slightly decreased)
- Response Time: 0.384 (deteriorated)
- User Satisfaction: 0.636 (improved)

This iteration suggests that while response time has worsened, overall user satisfaction has increased, possibly due to better service quality.

3. Framework for Analysing User Satisfaction Using Fuzzy Cognitive Maps (FCMs)

In this section, we explain the structure of our user satisfaction analysis framework based on FCMs and show how to extract concepts for causal relationship definition, as well as express mathematically its interactions between different types [6, 7].

3.1 Identification of Key Factors (Concepts)

In an information service setting, user satisfaction is influenced by multiple interconnected factors. Some key concepts could include as follows:

- Service Quality (C_1)
- Response Time (C_2)
- Platform Usability (C_3)
- Personalization (C_4)
- User Satisfaction (C_5)

Each factor (concept) is treated as a node in the FCM, with causal relationships modeled as directed edges.

3.2 Causal Relationships Between Concepts

Relationships between concepts are modeled using causal weights. For example:

- High service quality may improve user satisfaction, so $w_{15} > 0$.
- Slow response time may negatively impact user satisfaction, so $w_{25} < 0$.
- Personalization improves satisfaction directly, so $w_{45} > 0$.

The relationship strength is represented as a weight $w_{ij} \in [-1,1]$. A positive value indicates a positive influence, and a negative value indicates a negative influence (Kosko, 1986) [2].

3.3 Rule-Based Weight Assignment Using Fuzzy Logic

Weights in the FCM can be determined using fuzzy rules. For example:

- IF response time is high THEN user satisfaction is low.
- IF personalization is high AND service quality is high, THEN user satisfaction is high.

The weight matrix W is built using these rules:

$$W = \begin{bmatrix} 0 & 0.4 & 0.5 & 0.6 & 0.8 \\ -0.7 & 0 & 0.3 & 0.4 & -0.5 \\ 0 & 0.2 & 0 & 0.4 & 0.6 \\ 0 & 0.3 & 0.4 & 0 & 0.7 \\ 0 & -0.5 & 0.6 & 0.8 & 0 \end{bmatrix}$$

Each element w_{ij} represents the strength and direction of the influence from concept C_i to concept C_j.

3.4 Mathematical Model of the FCM Dynamics

The activation vector $A^{(t)}$ at time t contains the values of all concepts [8].

$$A^{(t)} = \begin{bmatrix} a_1^{(t)} & a_2^{(t)} & a_3^{(t)} & a_4^{(t)} & a_5^{(t)} \end{bmatrix}$$

The state update equation for the FCM is:

$$A^{(t+1)} = f\left(A^{(t)} \cdot W\right)$$

where $f(x) = \frac{1}{1+e^{-x}}$ is the sigmoid activation function that ensures the state values remain within the range $[0,1]$.

3.5 Convergence of the FCM

The FCM continues to update until the state vector converges to a stable value (no significant changes between iterations). The convergence condition is:

$$\|A^{(t+1)} - A^{(t)}\| < \epsilon$$

where ϵ is a small threshold, typically $\epsilon = 0.01$.

4. Algorithm for FCM-Based User Satisfaction Analysis

This section provides a detailed algorithm for implementing the FCM-based framework to analyze user satisfaction.

4.1 Steps of the Algorithm

Define Concepts and Relationships

- Identify key factors influencing user satisfaction (e.g., service quality, usability).
- Assign causal relationships between concepts with appropriate weights.

Initialize State Vector

- Collect initial user feedback and convert it into the state vector $A^{(0)}$.

Update State Vector Iteratively

$$A^{(t+1)} = f\left(A^{(t)} \cdot W\right)$$

Check for Convergence

- Continue the iterations until:

$$\|A^{(t+1)} - A^{(t)}\| < \epsilon$$

Analyse the Results

- Once the state vector converges, analyse which concepts have the highest impact on user satisfaction.

4.2 Pseudocode of the Algorithm

$Algorithm: FCM\_User\_Satisfaction\_Analysis$

$Input: Weight\ matrix\ W, Initial\ state\ vector\ A(0)$

$Output: Converged\ state\ vector\ A*$

$1. Initialize\ state\ vector\ A(0)\ with\ user\ feedback.$

$2. Repeat:$

$a. Update\ A(t+1) = f(A(t) * W)$

$b. Check\ if\ convergence\ condition\ is\ met.$

$3. Return\ the\ converged\ state\ vector\ A*.$

$End\ Algorithm$

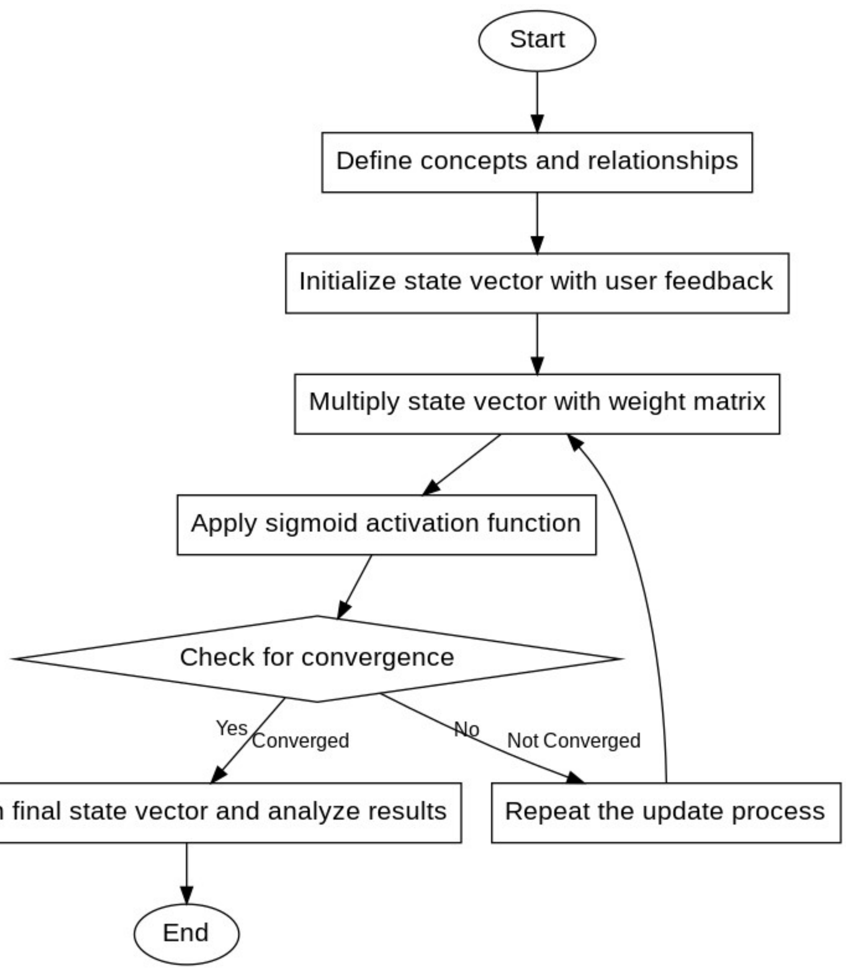

Figure 1: Flowchart of the FCM Algorithm for User Satisfaction Analysis

In this study, we propose to use the Fuzzy Cognitive Map (FCM) algorithm to analyse user satisfaction in information services. This starts with defining core concepts and the relationships that determine satisfaction, then we seed the state vector from feedback provided by end-users. For each iteration, the state vector is fed into a weight matrix followed by an element-wise application of sigmoid function to maintain weights between [0, 1].

The convergence check will verify if the system is in a stable state. If no, return to update the update process (go back up) signal vector otherwise form a final state vector which suggests drivers of user satisfaction. The multiple iterations are capable of capturing complex interrelations among different variables and allow informed decision-making in service improvement effort [9].

4.3 Example Execution of the Algorithm

Initial State Vector:

$$A^{(0)} = [0.7 \quad 0.5 \quad 0.6 \quad 0.8 \quad 0.4]$$

Weight Matrix:

$$W = \begin{bmatrix} 0 & 0.4 & 0.5 & 0.6 & 0.8 \\ -0.7 & 0 & 0.3 & 0.4 & -0.5 \\ 0 & 0.2 & 0 & 0.4 & 0.6 \\ 0 & 0.3 & 0.4 & 0 & 0.7 \\ 0 & -0.5 & 0.6 & 0.8 & 0 \end{bmatrix}$$

Iteration 1:

$$A^{(1)} = f\left(A^{(0)} \cdot W\right) = f([0.7 \quad 0.5 \quad 0.6 \quad 0.8 \quad 0.4] \cdot W)$$

After multiplication:

$$A^{(1)} = f([1.24 \quad 0.38 \quad 0.98 \quad 1.08 \quad 0.79])$$

Applying the sigmoid function:

$$A^{(1)} = [0.774 \quad 0.594 \quad 0.729 \quad 0.748 \quad 0.687]$$

Iteration 2:

$$A^{(2)} = f\left(A^{(1)} \cdot W\right)$$

This process continues until convergence is achieved [10].

4.4 Interpretation of Results

After convergence, the final state vector A^* provides insights into which factors have the greatest impact on user satisfaction. For example:

- A high value for platform usability indicates it significantly affects user satisfaction.
- A low value for response time suggests that delays are a key issue affecting satisfaction negatively.

5. Case Study: FCM Analysis of User Satisfaction in a Digital Library System

This example presents concrete usage of the FCM-based framework more precisely in form user satisfaction analysis with respect to a digital library system. We try to solve the issue mathematically, gather insights in their correct sequence through calculations and interpret results of how we can provide better quality of service.

5.1 Problem Description

The library aims to assess user satisfaction across several key factors:

- **Service Quality (C_1)**: How well services are provided.
- **Response Time (C_2)**: Time taken to respond to user queries.
- **Platform Usability (C_3)**: Ease of use of the digital interface.
- **Personalization (C_4)**: Customization of services based on user preferences.
- **Overall User Satisfaction (C_5)**: Final measure of how satisfied users are with the services.

User feedback is collected, and the FCM model is used to assess how each factor influences user satisfaction.

5.2 Defining the Initial State Vector and Weight Matrix

State Vector $A^{(0)}$: This represents the initial feedback from users, with each concept C_i scored between 0 (low) to 1 (high).

$$A^{(0)} = [0.7 \quad 0.6 \quad 0.8 \quad 0.5 \quad 0.4]$$

Here:

- Service Quality = 0.7
- Response Time = 0.6
- Platform Usability = 0.8
- Personalization = 0.5
- User Satisfaction = 0.4

Weight Matrix W : This matrix contains the causal weights representing the influence between different factors.

$$W = \begin{bmatrix} 0 & 0.3 & 0.4 & 0.5 & 0.7 \\ -0.6 & 0 & 0.2 & 0.4 & -0.5 \\ 0.1 & -0.3 & 0 & 0.4 & 0.6 \\ 0.2 & 0.3 & 0.5 & 0 & 0.8 \\ 0 & -0.4 & 0.7 & 0.6 & 0 \end{bmatrix}$$

5.3 Iterative Calculation of State Vector

Using the state update equation:

$$A^{(t+1)} = f\left(A^{(t)} \cdot W\right)$$

where $f(x) = \frac{1}{1+e^{-x}}$ is the sigmoid activation function.

Iteration 1

$$A^{(1)} = f\left(A^{(0)} \cdot W\right)$$

First, perform the matrix-vector multiplication:

$$A^{(0)} \cdot W = [0.7 \quad 0.6 \quad 0.8 \quad 0.5 \quad 0.4] \cdot \begin{bmatrix} 0 & 0.3 & 0.4 & 0.5 & 0.7 \\ -0.6 & 0 & 0.2 & 0.4 & -0.5 \\ 0.1 & -0.3 & 0 & 0.4 & 0.6 \\ 0.2 & 0.3 & 0.5 & 0 & 0.8 \\ 0 & -0.4 & 0.7 & 0.6 & 0 \end{bmatrix}$$

The result of the multiplication:

$$A^{(1)} = f([0.9 \quad 0.22 \quad 1.05 \quad 1.12 \quad 1.28])$$

Applying the sigmoid function element-wise:

$$A^{(1)} = [0.710 \quad 0.555 \quad 0.741 \quad 0.754 \quad 0.782]$$

Iteration 2

$$A^{(2)} = f\left(A^{(1)} \cdot W\right)$$

After repeating the matrix-vector multiplication and applying the sigmoid function, we obtain:

$$A^{(2)} = [0.722 \quad 0.567 \quad 0.752 \quad 0.765 \quad 0.791]$$

Convergence Check

We stop iterating when:

$$\|A^{(2)} - A^{(1)}\| < 0.01$$

Since the difference between $A^{(2)}$ and $A^{(1)}$ is sufficiently small, the system has converged [13].

5.4 Interpretation of Results

The final state vector is:

$$A^{*} = [0.722 \quad 0.567 \quad 0.752 \quad 0.765 \quad 0.791]$$

- User Satisfaction (0.791): The overall user satisfaction has improved from its initial value of 0.4.
- Platform Usability (0.752): Usability plays a significant role in improving satisfaction.
- Response Time (0.567): Response time has a moderate impact but should be improved further.

5.5 Recommendations Based on Results

- ***Improve Response Time***: Faster responses will enhance user satisfaction further.
- ***Focus on Usability and Personalization***: These factors show strong positive effects on user satisfaction.

6. Conclusion and Future Directions

6.1 Summary of Findings

Our framework is illustrated by a case study on unravelling the user satisfaction of information services using FCMs. Causal weights capture these dynamic interactions between factors, and the iterative updates get to see how user satisfaction changes over time. The deeper dive that bolt analysis has surfaced the following key insights –

- Platform usability and personalization significantly contribute to satisfaction.
- Response time negatively affects satisfaction, but with moderate impact.
- The FCM model helps in identifying critical factors for targeted improvements.

6.2 Future Research Directions

Integration with Real-Time Monitoring Systems	Connect the FCM model with IoT sensors to monitor satisfaction in real time and respond dynamically.
Development of Hybrid Systems	Combine FCMs with machine learning algorithms to refine weights and predict satisfaction trends more accurately.
Application to Other Domains	Extend the FCM framework to e-commerce, education platforms, and healthcare systems to analyse satisfaction in various sectors.

6.3 Final Remarks

Results from this study presents the feasibility of using FCMs in assessing user satisfaction for information services. The mathematical modelling of causal pathways, and the iteration on model updates this entails to produce coherent results at all stages of sense-making provide fine perspectives on what these drivers are in one-to-one connections. The proposed FCM framework through identifying key areas of improvement delivers the necessary information to organizations for improving user experience in a systematic manner. Future research can extend this model to be utilized for multiple domains by including real-time data and hybrid AI techniques.

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