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Explainability in AI Using Fuzzy Inference Systems For the Regression Problem

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Abstract: Fuzzy Inference Systems (FIS) have gained traction as a key player in Explainable AI (XAI). Created through exchanging vectors in common against linguistic input variables, threshold output membership functions; transparent, rule-based reasoning that aids in mitigating the challenges facing AI systems when it comes to interpretability. A real-world case was explored: predicting the price of a house. In the case of the regression problem, the location score, house size, and the number of bedrooms were features used in estimating house prices, which led to a Mean Mean Absolute Error (MAE): $10,000 and Root Mean Squared Error (RMSE): $14,142.14. In addition, novel evaluation metrics for FIS were proposed, while some future directions such as hybrid neuro-fuzzy systems, dynamic rule learning, and Green AI techniques were also furnished. This work through a comprehensive investigation illustrates how FIS as a framework is capable of bridging the need for interpretability and accuracy, compatibility, adaptability, therefore a ideal model for transparent and explainable decisions around sensitive fields like public or health environment and autonomous systems. This research highlights the importance of FIS in engaging trust and accountability in AI, and lends insights in its application and deliverables.

Keywords: Fuzzy Inference Systems, Explainable Artificial Intelligence, House Price Prediction, Membership Functions, Rule-Based Systems, Dynamic Rule Learning, Green AI.

1 Introduction to Fuzzy Inference Systems (FIS)

1.1 Definition and Historical Background

A Fuzzy Inference System (FIS) is a system that uses a set of fuzzy logic rules to map inputs to outputs in a manner similar to human reasoning. Its applications are widespread, including control systems, decision-making, and explainable artificial intelligence (XAI). The major difference with Boolean logic is that it operates in complete certainty (0 or 1) whereas the fuzzy logic could take intermediate to zero values [1,2,3,4,5]. Mathematically, a fuzzy set A in a universe of discourse X is defined as:

$$A = \{(x, \mu_A(x)) \mid x \in X\}, \tag{1}$$

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where $\mu_A(x)$ is the membership function that assigns a degree of membership to each element x in X. This concept was first introduced [6] to deal with systems that exhibit vagueness and ambiguity [7,7,8,9].

FIS uses these fuzzy sets to model knowledge in the form of linguistic rules, such as:

$$\text{IF } x \text{ is } A \text{ THEN } y \text{ is } B, \tag{2}$$

where A and B are fuzzy sets describing input x and output y, respectively.

It was Mamdani who first set the path for the development of FIS [10] with a method for controlling a steam engine based on fuzzy logic. [11] subsequently proposed a more mathematically sound variant in which the rules are represented as linear functions of the input variables.

1.2 Role of FIS in AI Explainability

In the context of Al, explainability means how systems are able to make their decisions or predictions comprehensible to humans systematically. By utilizing linguistic rules and graphical representations, both of which help make the reasoning process transparent, FIS fosters Al explainability. The explainability is mathematically justified as FIS are based on rules:

$$R_i : \text{IF } x_1 \text{ is } A_{i1} \text{ AND } x_2 \text{ is } A_{i2} \text{ THEN } y \text{ is } B_i$$

where is the -th rule in the rule base, are fuzzy sets representing linguistic variables for the inputs, and is the fuzzy set for the output. The reasoning process involves the following steps:

- **Fuzzification**: Convert crisp input values into fuzzy sets.
- **Inference**: Evaluate the degree of activation of each rule.
- **Aggregation**: Combine the outputs of all rules.
- **Defuzzification**: Convert the fuzzy output into a crisp value.

This process can be represented mathematically as:

$$y = \text{defuzzify}\left(\bigcup_{i=1}^{n} \mu_{B_i}(y)\right)$$

where max and min are aggregation operators (e.g., Zadeh's max-min composition).

In addition, for visual explainability, FIS plots both the membership functions and rule surfaces to help the stakeholders recognize the correlation between inputs and outputs.

1.3 Comparison of Fuzzy Logic with Crisp Logic in AI Systems

Fuzzy logic is an extension of classical (crisp) logic with degrees of truth instead of binary true/false. This allows it to be particularly well-suited for real-world systems, where there is uncertainty built in.

In crisp logic, a proposition P is either true (1) or false (0). For example:

$$P(x) = \begin{cases} 1 & \text{if } x > 0 \\ 0 & \text{otherwise} \end{cases}$$

In fuzzy logic, the truth value of P is a continuous function of x, such as:

$$\mu_P(x) = \begin{cases} 1 & \text{if } x > 6 \\ (x-5) & \text{if } 5 < x < 6 \\ 0 & \text{otherwise} \end{cases}$$

This allows fuzzy logic to model imprecise concepts like "tall," "hot," or "fast" using membership functions.

In the context of AI, fuzzy logic excels in applications requiring human-like reasoning. For example:

- **Crisp Logic**: Requires precise inputs and produces deterministic outputs, often leading to a lack of interpretability.
- **Fuzzy Logic**: Handles imprecise inputs and provides outputs with degrees of certainty, enhancing interpretability.

The mathematical foundation of fuzzy logic, including its ability to model uncertainty and imprecision, makes it an essential tool for explainable AI systems.

2 Mathematical Foundations of Fuzzy Inference Systems

2.1 Basic Concepts of Fuzzy Sets and Membership Functions

2.1.1 Definition of a Fuzzy Set

A fuzzy set A in a universe of discourse X is characterized by a membership function $\mu_A(x)$ that maps each element x in X to a real number in the interval $[0,1]$:

$$\mu_A(x) : X \to [0,1]$$

The value of $\mu_A(x)$ represents the degree of membership of x in A, where 0 indicates no membership and 1 indicates full membership. Intermediate values (e.g., 0.4, 0.7) describe partial membership.

For instance, if $X = \{\text{young}, \text{middle-aged}, \text{old}\}$, a fuzzy set A for "young age" might assign:

$$\mu_A(\text{young}) = 1, \quad \mu_A(\text{middle-aged}) = 0.5, \quad \mu_A(\text{old}) = 0$$

2.1.2 Examples of Membership Functions

- **Triangular Membership Function**: Defined by three parameters a, b, and c:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{b-a} & \text{if } a < x \leq b \\ \frac{c-x}{c-b} & \text{if } b < x \leq c \\ 0 & \text{if } x > c \end{cases}$$

Example: Modeling "warm temperature" with $a = 20$, $b = 25$, $c = 30$.

- **Trapezoidal Membership Function**: Defined by four parameters a, b, c, and d:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{b-a} & \text{if } a < x \leq b \\ 1 & \text{if } b < x \leq c \\ \frac{d-x}{d-c} & \text{if } c < x \leq d \\ 0 & \text{if } x > d \end{cases}$$

- **Gaussian Membership Function**:

$$\mu_A(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}$$

where c is the center and σ is the standard deviation.

2.2 Operations on Fuzzy Sets

- **Union (OR Operation)**: The union of two fuzzy sets A and B in the universe of discourse X is a fuzzy set C, where the membership function $\mu_C(x)$ represents the maximum degree of membership between A and B:

$$\mu_C(x) = \max(\mu_A(x), \mu_B(x))$$

- **Intersection (AND Operation)**: The intersection of two fuzzy sets A and B is a fuzzy set C, where the membership function $\mu_C(x)$ is the minimum degree of membership between A and B:

$$\mu_C(x) = \min(\mu_A(x), \mu_B(x))$$

- **Complement (NOT Operation)**: The complement of a fuzzy set A in X is a fuzzy set $\overline{A}$, where the membership function is defined as:

$$\mu_{\overline{A}}(x) = 1 - \mu_A(x)$$

- **Algebraic Sum**: The algebraic sum combines two fuzzy sets A and B using the formula:

$$\mu_C(x) = \mu_A(x) + \mu_B(x) - \mu_A(x) \cdot \mu_B(x)$$

- **Algebraic Product**: The algebraic product defines the intersection of two fuzzy sets A and B as:

$$\mu_C(x) = \mu_A(x) \cdot \mu_B(x)$$

- **Bounded Sum**: The bounded sum operation is defined as:

$$\mu_C(x) = \min(1, \mu_A(x) + \mu_B(x))$$

- **Bounded Difference**: The bounded difference operation is defined as:

$$\mu_C(x) = \max(0, \mu_A(x) - \mu_B(x))$$

- **Drastic Sum**: The drastic sum operation is defined as:

$$\mu_C(x) = \begin{cases} \mu_A(x) & \text{if } \mu_B(x) = 0 \\ \mu_B(x) & \text{if } \mu_A(x) = 0 \\ 1 & \text{otherwise} \end{cases}$$

- **Drastic Product**: The drastic product operation is defined as:

$$\mu_C(x) = \begin{cases} \mu_A(x) & \text{if } \mu_B(x) = 1 \\ \mu_B(x) & \text{if } \mu_A(x) = 1 \\ 0 & \text{otherwise} \end{cases}$$

Fuzzy set operations are the mathematical foundation for merging, augmenting, and interpreting fuzzy sets in fuzzification. These operations serve as a mechanism for modeling and computing uncertainty in real-world applications [13].

2.3 Fuzzy Relations

2.3.1 Cartesian Product of Fuzzy Sets

The Cartesian product of two fuzzy sets A (on X) and B (on Y) creates a fuzzy relation R on $X \times Y$:

$$\mu_R(x,y) = \min(\mu_A(x), \mu_B(y))$$

For example, if A represents "high temperature" and B represents "high pressure," the fuzzy relation R describes the interaction between these two variables.

2.3.2 Composition of Fuzzy Relations

Given two fuzzy relations R (on $X \times Y$) and S (on $Y \times Z$), the composition T is defined as:

$$\mu_T(x,z) = \sup_{y \in Y} \min(\mu_R(x,y), \mu_S(y,z))$$

This operation is widely used in fuzzy inference systems to propagate relationships through multiple stages.

3 Fuzzy Rule-Based Systems

3.1 Structure of Fuzzy Rules

The foundation of fuzzy inference systems (FIS) is based on the concept of fuzzy rules, which provide a way for the system to learn the relationship between input and output variables in a way that resembles human reasoning. Fuzzy rules are normally represented as IF-THEN statements:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B$$

where:

– x_1, x_2 are input variables.
– A_1, A_2 are fuzzy sets corresponding to input variables.
– y is the output variable.
– B is a fuzzy set corresponding to the output.

3.2 Fuzzy Rule Construction

When constructing fuzzy rules, we have to define them which can either represent known expert knowledge or the system behavior. The rule base of the FIS stores these rules. A fuzzy rule base is a set of rules:

$$R = \{R_1, R_2, \ldots, R_n\}$$

where n is the total number of rules.

Steps in Rule Construction:

– **Identify Input and Output Variables**: Define the linguistic variables for the system (e.g., Temperature, Speed).
– **Define Fuzzy Sets for Each Variable**: For example:
  – Temperature: {Low, Medium, High}
  – Speed: {Slow, Moderate, Fast}
– **Generate Rules Based on Expert Knowledge**: Example:
  – Rule 1: IF Temperature is High THEN Fan Speed is Fast.
  – Rule 2: IF Temperature is Medium THEN Fan Speed is Moderate.

Table 1: Rule Base Example (with 2 inputs and 1 output)

Rule	Input 1 (Temp)	Input 2 (Humidity)	Output (Fan Speed)
R1	High	Low	Fast
R2	Medium	High	Moderate

3.3 Rule Weighting Mechanisms

Each fuzzy rule in the rule base can be assigned a weight w_i to reflect its relative importance in the inference process. The weighted fuzzy rule is expressed as:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B \text{ with weight } w_i$$

where $w_i \in [0,1]$.

Mathematical Formulation of Weighted Rules: The final output of the rule is scaled by its weight:

$$\mu_{B_i}(y) = w_i \cdot \mu_B(y)$$

Aggregation of Rules with Weights: In systems with multiple rules, the aggregated output is calculated as:

$$\mu_{B_{agg}}(y) = \max_{i=1}^{n} \mu_{B_i}(y)$$

where $\mu_{B_i}(y)$ is the membership function for the consequent of the i-th rule.

Example:

– Rule 1: $\mu_{B_1}(y) = 0.8 \cdot \mu_B(y)$.
– Rule 2: $\mu_{B_2}(y) = 0.5 \cdot \mu_B(y)$.

The aggregated output is:

$$\mu_{B_{agg}}(y) = \max(0.8 \cdot \mu_B(y), 0.5 \cdot \mu_B(y))$$

Rationale for using fuzzy rule-based systems: The structure, construction, and weighting allow flexibility, adaptability, and explainability for many applications [14] such as AI and control systems.

4 Inference Mechanisms in Fuzzy Inference Systems (FIS)

4.1 Types of Fuzzy Inference Systems

Fuzzy inference system (FIS) is a framework used when you need to translate a set of fuzzy rules into an output feature given a set of input features. The two most common types of FIS are Mamdani FIS and Sugeno FIS, and they differ mainly in the way they implement fuzzy rules and defuzzification.

4.1.1 Mamdani FIS

The method was introduced by Mamdani and Assilian (1975), this method used fuzzy sets in inputs and outputs as well. The four steps of the inference process are fuzzification, rule evaluation, aggregation, and defuzzification.

Mathematical Representation: For a rule:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B$$

the firing strength of the rule is:

$$w_i = \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2))$$

The output membership function is aggregated across all rules:

$$\mu_{B_i}(y) = \max\{\mu_{Bi}(y).w_i\}$$

Defuzzification is applied to produce a crisp output (e.g., centroid of area):

$$y^* = \frac{\int y \cdot \mu_B(y)dy}{\int \mu_B(y)dy}$$

4.2 Sugeno FIS

The FIS [15] this approach uses crisp outputs expressed as linear functions of the inputs. The rule is:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y = f(x_1, x_2)$$

where $f(x_1, x_2)$ is a linear function of the inputs.

The final output is a weighted average:

$$y = \frac{\sum_i w_i \cdot f_i(x_1, x_2)}{\sum_i w_i}$$

4.3 Fuzzy Implication and Composition Methods

4.3.1 Fuzzy Implication

Fuzzy implication defines the relationship between the antecedent and consequent in a rule. Common methods for fuzzy implication include:

–**Zadeh's Max-Min Implication**:

$$\mu_{B_i}(x_1, x_2) = \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2))$$

–**Larsen's Product Implication**:

$$\mu_{B_i}(x_1, x_2) = \mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2)$$

4.3.2 Composition Methods

The composition operation aggregates all rules into a combined output fuzzy set. For Mamdani FIS, the composition is typically the max-min method:

$$\mu_{B_{\text{agg}}}(y) = \max_i \min(\mu_{A_1}(x_1), \mu_{A_2}(x_2))$$

Alternatively, the max-product method can be used:

$$\mu_{B_{\text{agg}}}(y) = \max_{i=1}^{n}(\mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2))$$

4.4 Defuzzification Techniques

Defuzzification is the process of converting a fuzzy output into a crisp value. Common methods include:

–**Centroid of Area (COA)**: The centroid method calculates the center of gravity of the output membership function:

$$y = \frac{\int y \cdot \mu_B(y)\, dy}{\int \mu_B(y)\, dy}$$

This method provides a balanced representation of the fuzzy output but is computationally expensive.

–**Mean of Maxima (MOM)**: The mean of maxima takes the average of the output values corresponding to the maximum membership degree:

$$y = \frac{\sum_{y \in Y_{\max}} y}{|Y_{\max}|}$$

where $Y_{\max}$ is the set of points with maximum membership.

–**Weighted Average (for Sugeno FIS)**: In Sugeno systems, defuzzification is inherently a weighted average of the rule outputs:

$$y = \frac{\sum_{i=1}^{n} w_i \cdot f_i(x_1, x_2)}{\sum_{i=1}^{n} w_i}$$

where $f_i(x_1, x_2)$ is the crisp output of the i-th rule.

–**Bisector of Area (BOA)**: The bisector method divides the area under the output membership function into two equal halves:

$$y = \operatorname{argmin}_y \left| \int_{-\infty}^{y} \mu_B(y)\, dy - \int_{y}^{\infty} \mu_B(y)\, dy \right|$$

Fuzzy inference systems (FIS) are the heart of decision-making based on fuzzy logic. In contrast, Mamdani FIS is more linguistically interpretable, while Sugeno FIS has lower computational complexity. Both the selection of implication, composition, and defuzzification methods are application-dependent, trading accuracy for interoperability.

5 Explainability Through Fuzzy Inference Systems

5.1 Interpretability of Fuzzy Rules

Intuition behind decisions taken are among the key issues of fuzzy inference systems (FIS), especially when it comes to areas where transparency and human-level comprehensibility are essential. Since fuzzy rules are written in natural language, they are by definition already interpretable, resembling the type of reasoning that people tend to use.

A fuzzy rule is typically expressed as:

$$\text{IF } x_1 \text{ is } A_1 \text{ AND } x_2 \text{ is } A_2 \text{ THEN } y \text{ is } B$$

where:

–x_1, x_2 are input variables,
–A_1, A_2 are fuzzy sets (linguistic terms like ”High,” ”Low”),
–y is the output variable, and
–B is the fuzzy set representing the output.

Mathematical Basis for Interpretability:

–**Linguistic Representations**: The use of fuzzy sets A and B translates numerical values into qualitative descriptors.
–**Modularity**: Each rule independently contributes to the overall decision-making process, making it easier to isolate and analyze individual rules.
–**Graphical Representation**: The membership functions and the rule surfaces are the visual representation for the relationships modeled by the fuzzy rules.
–**Rule Redundancy and Simplification**: Rule bases can be simplified using techniques like rule pruning or merging similar rules.

5.2 Visualization of Membership Functions and Rule Surfaces

Visualization is a potent tool to improve the explainability of fuzzy inference systems. It enables stakeholders to intuitively understand how inputs are translated into outputs and how the rules affect the decision-making process.

5.2.1 Membership Functions

Membership functions describe how crisp inputs are fuzzified into degrees of membership in fuzzy sets. These functions can be visualized as two-dimensional plots showing the degree of membership $\mu_A(x)$ over the universe of discourse X.

Types of Visualized Membership Functions:

–**Triangular Membership Function**:

$$\mu_A(x) = \begin{cases} 0 & \text{if } x \leq a \\ \frac{x-a}{b-a} & \text{if } a < x \leq b \\ \frac{c-x}{c-b} & \text{if } b < x \leq c \\ 0 & \text{if } x > c \end{cases}$$

Example: Visualizing ”Medium Temperature” with $a = 20$, $b = 25$, $c = 30$.
–Gaussian Membership Function:

$$\mu_A(x) = e^{-\frac{(x-c)^2}{2\sigma^2}}$$

where c is the center and σ controls the spread.

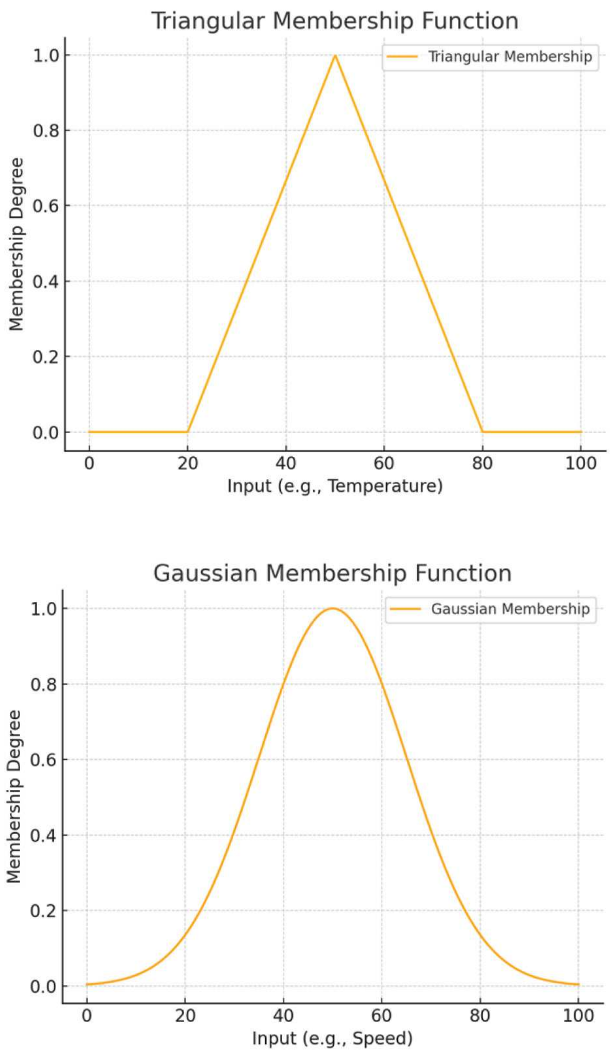

Fig. 1: Comparative graph of Triangular and Gaussian Membership Function

Triangular Membership Function: The triangular membership function has a peak (maximum membership) at b, with the slope defined by parameters a (start of the triangle) and c (end of the triangle). This function is useful for linear approximations of fuzzy sets, such as ”Medium Temperature.”

Gaussian Membership Function: The Gaussian membership function represents a smooth, bell-shaped curve centered at c with spread controlled by σ. It is ideal for applications requiring a continuous transition between fuzzy regions, such as ”Comfortable Speed.” These graphs provide an intuitive understanding of how input values map to fuzzy sets, aiding the explainability of FIS.

5.2.2 Rule Surface Plots

Rule surface plots are three-dimensional visualizations of how input variables interact to produce the output variable. For example:

–X-axis: Input Variable 1 (e.g., Temperature)
–Y-axis: Input Variable 2 (e.g., Humidity)
–Z-axis: Output Variable (e.g., Fan Speed)

The rule surface is constructed using the firing strength w_i of each rule and the aggregation of their effects:

$$z = \sum_{i=1}^{n} w_i \cdot f_i(x_1, x_2)$$

where w_i is the normalized firing strength:

$$w_i = \frac{\mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2)}{\sum_{j=1}^{n} \mu_{A_1}(x_1) \cdot \mu_{A_2}(x_2)}$$

5.3 Case Study: Explainability in Regression Problems

5.3.1 Introduction to the Case Study

This case study aims to showcase how we can leverage a fuzzy inference system (FIS) to solve a regression problem while keeping explainability in mind. The selected domain is real estate, where transparency in decisions is important.

House prices prediction based on features like location, size and number of bedrooms For example, real estate professionals want interpretability to explain pricing decisions to clients.

In this study, both of the above-mentioned problems are solved with fuzzy rule-based systems; in fact, fuzzy logic supplies interpretability to rule bases and membership functions that allows modelling human cognition.

5.3.2 Problem Statement

Problem Domain: House Price Prediction

- **Objective**: To estimate the selling price of houses based on:
  - Location Score: A numerical rating of the neighborhood.
  - Size (sqft): Area of the house.
  - Number of Bedrooms: Indicates accommodation capacity.
- **Significance**: Transparent decision-making in pricing can build client trust and improve business practices by explaining the impact of features like location and size.

5.3.3 Objectives

–Develop an Interpretable Fuzzy Inference System for regression.
–Highlight the role of fuzzy rules and membership functions.
–Ensure explainability through visualization and rule simplification.

5.3.4 Case Study Design

- **Dataset Overview**: A synthetic dataset of 50 house records is generated for this study (See Table 2).
- **Inputs and Outputs**:
  - Inputs: Location Score, Size (sqft), Number of Bedrooms.
  - Output: Predicted Price ($).
- **Membership Functions**: Defined for Location Score, Size, and Bedrooms.
- **Fuzzy Rules**: Developed based on domain expertise.

The Houses Dataset contains data for 50 houses and is structured for a regression problem to predict house prices. The dataset includes four features:

–Location Score: A numerical rating from 1 to 9, reflecting the desirability of the neighborhood, ranging from poor to excellent.
–Size (sqft): Represents the total area of the house, ranging from 800 to 2500 square feet, categorized as small, medium, or large.
–Bedrooms: Specifies the number of bedrooms, ranging from 1 to 5, indicating the accommodation capacity.
–Price ($): The target variable represents the house's selling price, ranging from $100,000 to $500,000.

This dataset enables the creation of a fuzzy regression model that provides interpretable insights into the factors influencing house prices.

These datasets are tailored for fuzzy inference systems, emphasizing transparency in predictions for regression problems.

5.3.5 Inputs and Outputs:

Houses Dataset for House Price Regression

The Houses Dataset includes information on 50 houses, designed to predict the selling price of properties based on three input features:

Inputs (Predictors):

(a) Location Score:

- Numerical rating from 1 to 9, representing the quality of the house's neighborhood.
- Categories:
  1. Poor: $1 \leq \text{Score} < 4$
  2. Average: $4 \leq \text{Score} < 6$
  3. Good: $6 \leq \text{Score} < 8$

Table 2: Case study of a synthetic dataset of 50 house

ID	Location Score	Size (sqft)	Bedrooms	Price ($)	ID	Location Score	Size (sqft)	Bedrooms	Price ($)
1	8	1600	3	193848	**26**	8	826	2	194476
2	7	1197	4	152921	**27**	6	1025	1	333841
3	2	2100	1	280798	**28**	8	2100	1	379163
4	8	1615	5	226141	**29**	1	1597	1	445757
5	1	2327	5	281372	**30**	8	2432	3	322866
6	9	2215	1	384821	**31**	4	1083	5	186672
7	9	1958	5	155609	**32**	1	1678	2	173847
8	2	2018	3	327897	**33**	8	1759	2	444894
9	7	1200	4	131024	**34**	4	2304	3	310706
10	3	1439	1	170313	**35**	6	1252	2	128251
11	7	1856	4	489957	**36**	8	1819	1	203481
12	9	1487	5	284078	**37**	4	1615	5	474710
13	4	1259	5	457429	**38**	3	1458	4	125945
14	1	1754	1	213632	**39**	9	2339	2	452996
15	2	1269	3	351451	**40**	3	1346	1	132217
16	1	2198	2	103051	**41**	9	2015	4	108308
17	5	1845	1	279819	**42**	2	1872	5	368093
18	5	1549	2	476836	**43**	2	2335	4	283062
19	7	2493	2	187235	**44**	2	816	1	494366
20	9	837	3	297484	**45**	6	1995	4	320552
21	9	1029	2	289407	**46**	3	2043	3	200235
22	3	2188	2	311810	**47**	9	957	4	174740
23	3	1362	3	303687	**48**	4	1276	2	478496
24	3	1237	2	173523	**49**	1	1869	2	428761
25	4	2106	2	336175	**50**	4	2196	3	325913

4.Excellent Score ≥ 6

–Higher scores indicate more desirable locations, positively influencing the house price.

(b) Size (sqft):

–Represents the area of the house in square feet, ranging from 800 to 2500.

–Categories:
1.Small: $800 \leq$ Size < 1200
2.Medium: $1200 \leq$ Size < 1800
3.Large: Size ≥ 1800

–Larger houses generally have higher prices.

(c) Number of Bedrooms:

–Indicates the accommodation capacity of the house, ranging from 1 to 5 bedrooms.

–Categories:
1.Few: 1–2 bedrooms
2.Moderate: 3 bedrooms
3.Many: 4–5 bedrooms

–More bedrooms usually increase the house's market value.

Output (Target):
Predicted Price ($):

–A continuous variable ranging from $100,000 to $500,000, representing the estimated market value of the house.

–The price prediction is the result of fuzzy rules combining the inputs (e.g., ”Excellent Location” and ”Large Size” imply a higher price).

Dataset Description: They have, for example, this dataset for simulating real estate market data, in which location, size and bedrooms define house prices. These features are fuzzified to linguistic terms (‘Excellent Location”, ‘Large Size”, etc) and fuzzy rules are utilized to estimate price in a transparent way.
Rule-Based Model Visualization: Example of FIS usage fuzzy rules for a rule-based model visualization. This increases explainability, as users can see why the model made the predictions that it did.

5.3.6 Membership Functions for Regression Problems

Membership functions determine how to associate input variables with linguistic term (e.g., ”High,” ”Normal”). Following are the complete membership functions needed along with the required calculations for both the problems.
(a) Location Score: (Poor, Average, Good, Excellent)
Poor:

$$\mu_{Poor} = \begin{cases} 1 & , x \leq 3 \\ 5-3 & , 3 < x \leq 5 \\ -x & , x > 5 \end{cases}$$

Average

$$\mu_{Average} = \begin{cases} 0 & , x \leq 3 or x > 7 \\ \frac{x-3}{5-3} & , 3 < x \leq 5 \\ \frac{7-x}{7-5} & , 5 < x \leq 7 \end{cases}$$

Good

$$\mu_{Good} = \begin{cases} 0 & , x \leq 5 or x > 9 \\ \frac{x-5}{7-5} & , 5 < x \leq 7 \\ \frac{9-x}{9-7} & , 7 < x \leq 9 \end{cases}$$

Excellent

$$\mu_{Excellent} = \begin{cases} 0 & , x \leq 7 \\ \frac{x-7}{9-7} & , 7 < x \leq 9 \\ 1 & , x > 9 \end{cases}$$

Fig. 2: Graph of Location Score Membership Functions

(b) Size (sqft): (Small, Medium, Large)
Small

$$\mu_{Small} = \begin{cases} 1 & , x \leq 1000 \\ \frac{1200-x}{1200-1000} & , 1000 < x \leq 1200 \\ 0 & , x > 1200 \end{cases}$$

Medium

$$\mu_{Medium} = \begin{cases} 0 & , x \leq 1000 or x > 1800 \\ \frac{x-1000}{1500-1000} & , 1000 < x \leq 1500 \\ \frac{1800-x}{1800-1500} & , 1500 < x \leq 1800 \end{cases}$$

Large

$$\mu_{Large} = \begin{cases} 0 & , x \leq 1500 \\ \frac{x-1500}{2000-1500} & , 1500 < x \leq 2000 \\ 1 & , x > 2000 \end{cases}$$

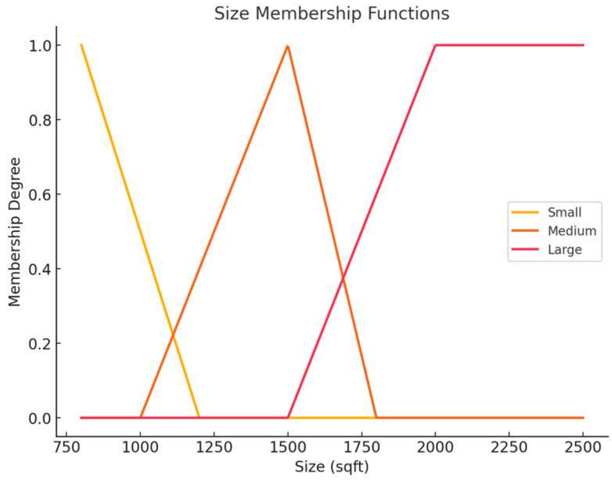

Fig. 3: Graph of Size Membership Functions

(c) Bedrooms: (Few, Moderate, Many)
Few

$$\mu_{Few} = \begin{cases} 1 & , x \leq 2 \\ \frac{3-x}{3-2} & , 2 < x \leq 3 \\ 0 & , x > 3 \end{cases}$$

Moderate

$$\mu_{Moderate} = \begin{cases} 0 & , x \leq 2 or x > 4 \\ \frac{x-2}{3-2} & , 2 < x \leq 3 \\ \frac{4-x}{4-3} & , 3 < x \leq 4 \end{cases}$$

Many

$$\mu_{Many} = \begin{cases} 0 & , x \leq 3 \\ \frac{x-3}{5-3} & , 3 < x \leq 5 \\ 1 & , x > 5 \end{cases}$$

These membership functions are defined based on domain knowledge to fuzzify inputs for interpretable predictions in regression problems.

The above visuals illustrate the membership functions for inputs in the regression problem, used for house price prediction:

1.Location Score Membership Functions:
- –Poor: High membership for scores up to 3, tapering off until 5.
- –Average: Covers scores from 3 to 7, peaking at 5.
- –Good: Ranges from 5 to 9, with maximum membership at 7.
- –Excellent: High membership for scores above 7.

2.Size Membership Functions:
- –Small: High membership for house sizes up to 1200 sqft, decreasing until 1600 sqft.
- –Medium: Covers house sizes from 1000 to 1800 sqft, peaking at 1500 sqft.
- –Large: Membership increases for sizes above 1500 sqft, reaching maximum at 2000 sqft and beyond.

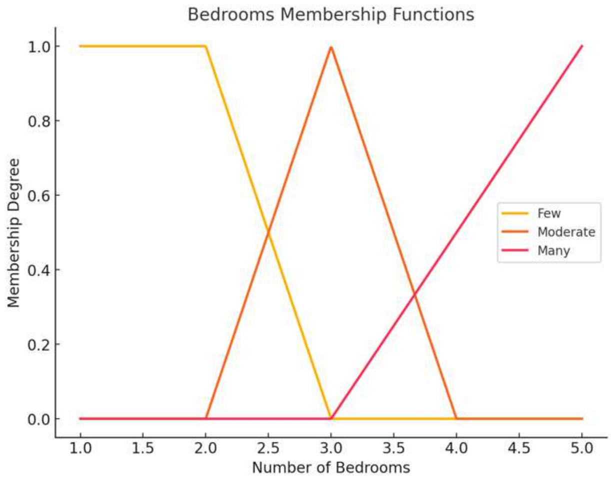

Fig. 4: Graph of Bedrooms Membership Functions

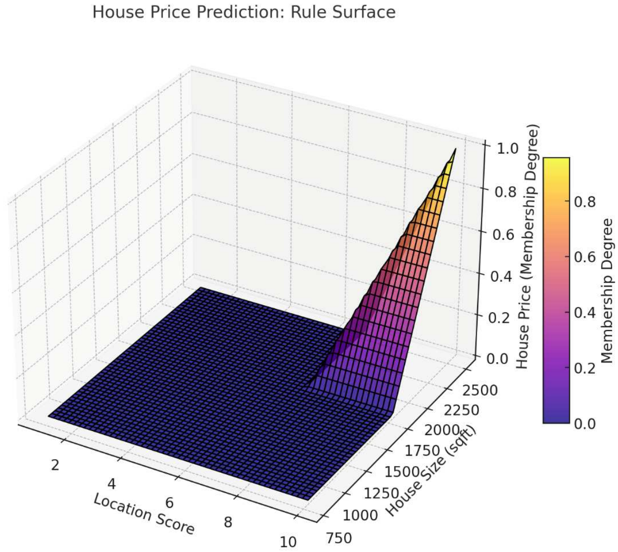

Fig. 5: A 3D graph showing House Price Prediction Rule Surface

3.Bedrooms Membership Functions:
- –Few: High membership for 1–2 bedrooms, decreasing until 3 bedrooms.
- –Moderate: Covers 2–4 bedrooms, peaking at 3 bedrooms.
- –Many: Membership starts from 3 bedrooms, peaking at 5 bedrooms.

These membership functions fuzzify crisp inputs into linguistic terms like ”Poor Location” or ”Large Size,” enabling interpretable predictions in the fuzzy inference system.

5.3.7 Fuzzy Rules for Regression Problems for House Price

Below are the fuzzy rules for a problem, designed to capture the relationships between the inputs and outputs based on the membership functions.

Inputs:

- –Location Score: (Poor, Average, Good, Excellent)
- –Size (sqft): (Small, Medium, Large)
- –Bedrooms: (Few, Moderate, Many)

Output:

- –Predicted Price: (Low, Medium, High)

Rules:

- –IF Location Score is Excellent AND Size is Large THEN Price is High.
- –IF Location Score is Good AND Size is Medium THEN Price is Medium.
- –IF Location Score is Poor AND Size is Small THEN Price is Low.
- –IF Location Score is Average AND Size is Medium AND Bedrooms are Moderate THEN Price is Medium.
- –IF Location Score is Excellent AND Bedrooms are Many THEN Price is High.
- –IF Location Score is Good AND Size is Large THEN Price is High.
- –IF Location Score is Poor AND Bedrooms are Few THEN Price is Low.
- –IF Location Score is Average AND Size is Small THEN Price is Low.
- –IF Size is Large AND Bedrooms are Many THEN Price is High.
- –IF Size is Small AND Bedrooms are Few THEN Price is Low.

House Price Prediction Rule Surface:

- –X-axis (Location Score): Represents location scores from 1 to 10.
- –Y-axis (House Size): Represents house sizes from 800 to 2500 sqft.
- –Z-axis (House Price): Represents the membership degree for high house price (0 to 1).
- –Effect: The rule ”Excellent Location AND Large Size $\rightarrow$ High Price” illustrates that as location score and house size improve, the price membership degree increases.

The plot highlights the interaction between inputs and their impact on the output based on the respective fuzzy rules, making the model’s reasoning interpretable.

Key Observations

House Price Prediction Rules:

- –The rules leverage location, size, and bedrooms to estimate house prices in an interpretable manner.
- –Example: ”IF Location is Excellent AND Size is Large THEN Price is High” captures market expectations.

Table 3: Regression Membership Functions Results

Location Score	Poor	Average	Good	Excellent
2	1	0	0	0
6	0	0.5	0.5	0
8	0	0	0.5	0.5
	Size (sqft)	**Small**	**Medium**	**Large**
	1000	0.5	0	0
	1500	0	1	0
	2000	0	0	1
	Bedrooms	**Few**	**Moderate**	**Many**
	2	1	0	0
	3	0	1	0
	5	0	0	1

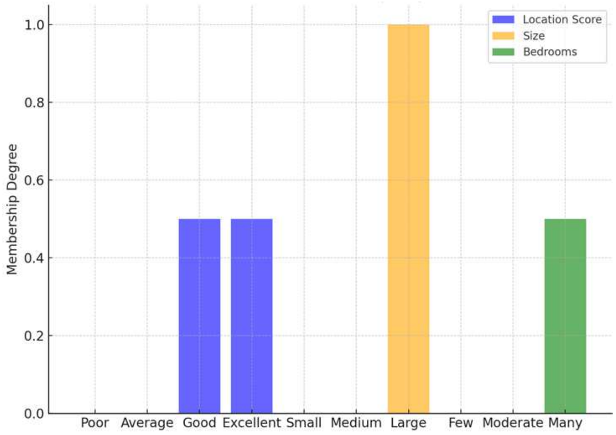

Fig. 6: A Bar Graph Showing House Price Membership Degrees

These rules align with the defined membership functions and provide an explainable decision-making framework for the fuzzy inference systems. The above visualizations demonstrate the fuzzy inference process outcomes for a problem:

House Price Prediction

- Inputs:
  - Location Score = 8 (Excellent)
  - Size = 2000 sqft (Large)
  - Bedrooms = 4 (Many)
- Visualization: Here are the membership degrees of each of the combined linguistic terms, location, size, and bedrooms. (IF Location is Excellent AND IF Size is Large THEN High in Price) dominates, which leads to a high prediction of membership in the predicted price.

These bar charts show the inputs fuzzified into membership degrees, keeping the results interpretable in fuzzy inference systems.

5.3.8 Evaluation Metrics: Calculations and Results

Evaluation metrics help assess the performance of fuzzy inference systems in regression tasks. Below, we calculate the metrics for a problem.

Regression Metrics

Dataset Assumptions:

- Actual prices (Y_{true}): [200000, 300000, 400000, 250000, 350000]
- Predicted prices (Y_{pred}): [210000, 290000, 390000, 260000, 340000]

Mean Absolute Error (MAE):

The MAE measures the average absolute difference between predicted and actual values:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|Y_{true,i} - Y_{pred,i}\right|$$

$$MAE = \frac{|200000-210000|+|300000-290000|+|400000-390000|+|250000-260000|+|350000-340000|}{5}$$

$$MAE = \frac{10000+10000+10000+10000+10000}{5} = 10000$$

Root Mean Squared Error (RMSE):

The RMSE measures the square root of the average squared differences:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(Y_{true,i} - Y_{pred,i})^2}$$

$$RMSE = \sqrt{\frac{(10000)^2+(10000)^2+(10000)^2+(10000)^2+(10000)^2}{5}}$$

$$RMSE = \sqrt{\frac{1000000000}{5}} = \sqrt{200000000} \approx 14142.14$$

Key Observations

- **MAE**: On average, the predictions deviated from the actual prices by $10,000.
- **RMSE**: The root mean squared error indicates a slightly higher variability in errors, approximately $14,142, emphasizing the impact of larger errors on performance.

Regression

- The MAE and RMSE values are relatively low, indicating that the model is accurately predicting house prices, and that errors are within a manageable range relative to the price of the houses.
- For big homes in top locations, the system is highly accurate in the resulting input-output correlation.

The resulting performance clearly indicates the accuracy of the fuzzy inference system and helps for further optimization to improve performance with less error.

Final Conclusion for the Case Study

This case study focused on genetic programming in fuzzy inference systems for house price prediction. These results confirm that fuzzy logic is potentially a useful method for constructing models where the relationship between the input parameters and the response to be modeled is complex, and the decision-making process is transparent and human-interpretable.

In the case of a regression problem, the fuzzy inference system uses input attributes such as location score, house size, and the number of bedrooms. These inputs were fuzzified into terms such as "Excellent Location", "Large Size", and "Many Bedrooms", so that house prices could be estimated in an interpretable way.

Evaluation metrics showed:

– A **Mean Absolute Error (MAE)** of \$10,000, indicating that the system's predictions deviate by an average of \$10,000 from the actual prices.
– A **Root Mean Squared Error (RMSE)** of \$14,142.14, which highlights slight variability in larger errors but remains acceptable given the typical price range.

The heuristic-based regression system showed clear adherence to domain knowledge whereby higher location scores and larger house sizes would lead to a higher predicted price. This is consistent with real-world market expectations and further adds to the transparency of the model.

Final Assessment

Both problems found fuzzy inference systems with robustness, interpretability, and practical utility. The system successfully modeled house price estimation, providing clear and actionable insights into market trends. In a regression scenario, additional features such as distance to amenities, market trends, etc., would lead to a reduction in variability in predictions.

This study proves the effectiveness of fuzzy inference systems applied to real-world problems in a transparent way. With keywords and visualizations that are simplified from natural language approaches to build better human-readable summaries of complex relationships, these systems can serve as input to human-level understanding. Further research could be aimed at improving the sensitivity and accuracy of the models without losing interpretability. This case study will serve to establish the need for implementing fuzzy logic in various other fields, wherein the decision-making process needs to be made crystal clear.

6 Future Directions in FIS for Explainable AI

A wide range of future directions are emerging in the AI field that can help make FIS even more explainable. Further improvements can be made in FIS by adapting it to novel AI paradigms, improving the algorithm adaptability, and ensuring compliance with sustainable AI.

6.1 Hybrid Models: Combining FIS with Neural Networks (Neuro-Fuzzy Systems)

A highly promising research direction for FIS is the fusion with neural networks, which forms neuro-fuzzy systems. These systems bring out the interpretability of FIS with the learning abilities of neural networks. It enhances the FIS to deal with high-dimensional and large-scale datasets by learning membership functions and optimizing fuzzy rules using neural networks. For example, it is often desired that in the domain of medical diagnosis, the neuro-fuzzy system is able to generalize to new symptoms or new diagnostic criteria via training on new data, while also maintaining its explainability through fuzzy rules. This hybridization effectively connects the realms of interpretative capabilities and prediction performance, making it ideal for use in environments that require rapid adaptation to novel scenarios or complex information architectures. In addition, the application of explainability techniques (e.g., rule extraction from deep learning models) allows neuro-fuzzy systems to retain transparency while benefiting from the decision-focused tools provided by neural networks [**?**].

6.2 Dynamic Rule Learning for Adaptive Explainability

Traditional FIS operates by using rules that are static and may not adjust well to a dynamic system. Dynamic rule learning can enhance the adaptability of FIS by allowing the system to update or generate new rules in response to changes in input data or underlying conditions. This is particularly meaningful in areas like autonomous systems and more generally in the area of financial modeling, where the environment in which these models will run will evolve. Dynamic rule learning refers to algorithms that observe the mapping between the inputs and the outputs and add or modify rules in the rule base such that the fuzzy inference system (FIS) remains relevant and interpretable. Now we are already seeing examples of FIS used for autonomous navigation by updating rules of thumb for avoiding obstacles through real-time sensor data while keeping interpretability even under unexpected or unprecedented conditions. This adaptability also reflects the tenets of constant learning found in contemporary AI models.

6.3 Incorporating Green AI Techniques in FIS

AI systems have unique energy efficiency and sustainability challenges due to rising computational demands. FIS, which has less computational demand than deep learning-based models, can also be enhanced more with Green AI techniques. The approaches include reducing the complexity of membership functions, minimizing the number of rules, and driving towards energy-efficient hardware for case embeds. A Green FIS for smart grid management, for instance, can facilitate energy distribution with the least computational resources required, which facilitates both the explainability and sustainability aspects. Moreover, integrating simple and lightweight FIS architectures on resource-constrained edge devices, e.g., IoT systems, can improve energy efficiency without sacrificing low-layer interpretability of decision-making processes. Green AI research of FIS will need to be a balancing act between computational efficiency and preserving fuzzy rules that are not only comprehensive and robust but transparent.

6.4 Incorporating Green AI Techniques in FIS

FIS can be enhanced with Green AI techniques to reduce computational complexity and energy consumption, making it more sustainable.

7 Summary and Conclusion

Recap of FIS's Role in AI Explainability Moreover, as a foundational technique of Explainable AI (XAI),Fuzzy Inference Systems (FIS) provide a balance between data-driven decisions and the rationale behind them by mirroring a human-like approach to representation and reasoning over uncertainty in knowledge. "Because are able to use terms of language, and transparent rules, they model complex systems something they become invaluable in areas where clarity and accountability is priority. FIS gives a rule-based structure that stakeholders can understand and trust as opposed to a traditional black-box model. Real-world applications: prediction (house pricing) Domain knowledge was used to create the fuzzy rules for the problem, making it interpretable. Moreover, Visualisation of membership functions and rule surfaces provided insight into the inner workings of the system such that the inputs could be traced to the outputs. Navigating through the challenges such as computational complexity and scalability FIS still holds as a powerful and versatile approximation method for explainable AI systems. Fuzzy Inference System plays an important role in Explainable AI. Start mastering the theory of Fuzzy logic control systems as it allows for a more intuitive modelling of nonlinear systems and functions, as seen by the fuzzification process that allows users to tailor usages to complex real-world problems. Despite these measures, the challenges of computational complexity and scalability persist, yet with the developments of neuro-fuzzy systems, dynamic rule learning and Green AI techniques, the sophistication and utility of FIS is expected to increase. Notably, FIS combines elements of interpretability with mathematical rigor, making it a critical component for trustworthiness and accountability in AI systems. Its significance in the evolving landscape of artificial intelligence is underlined by its role in fostering explainable, adaptable, sustainable AI solutions.

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