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An Empirical Approach to Fuzzy Logic System and Its Applications to Handle the Uncertainties and Identify the Complexities Inherent in Risk Assessment System for Decision-Making

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Abstract: Fuzzy logic provides a method to transform subjective risk assessments into a structured and quantifiable decision-making process. This process includes fuzzifying inputs, applying fuzzy rules, aggregating results, and defuzzifying the output to yield a crisp risk score. By managing uncertainty and imprecision, fuzzy logic proves to be a powerful tool in risk assessment. The Mamdani inference method, in particular, offers a systematic approach to combining fuzzy rules and generating a fuzzy output, which is then defuzzified into a precise risk value. This approach effectively addresses the complexities and uncertainties in risk assessment, enhancing decision-making capabilities. Fuzzy logic, distinct from classical binary logic, offers a framework for reasoning that accommodates approximation rather than fixed, exact values. An FIS involves fuzzification, rule evaluation, aggregation of outputs, and defuzzification to convert fuzzy inputs to crisp outputs. Different types of FIS, like the Mamdani FIS, employ fuzzy sets in their operations to manage and interpret imprecise data effectively.

Keywords: Fuzzy logic, Membership Functions, Defuzzification, and Mamdani inference

Introduction:

Understanding fuzzy logic involves grasping the fundamental concepts that distinguish it from classical binary logic. Fuzzy logic is a form of many-valued logic derived from fuzzy set theory to handle reasoning that is approximate rather than fixed and exact [1]. Here's a breakdown of the key components and principles of fuzzy logic: Fuzzy Sets - Classical Set: An element either belongs or does not belong to a set (binary membership: 0 or 1). A fuzzy Set is an element that can partially belong to a set with a degree of membership ranging between 0 and 1[2]. For example, the degree of membership for an element (x) in a fuzzy set (A) might be denoted as (mu_A(x)). Membership Functions: These functions define how each point in the input space is mapped to a membership value between 0 and 1. Common shapes of membership functions include triangular, trapezoidal, and Gaussian. Linguistic Variables [3]: These are variables described in terms of words or sentences from natural language rather than numerical values. For example, temperature might be described as "cold," "warm," or "hot." Fuzzy Rules

Fuzzy logic systems often use "if-then" rules to derive conclusions from fuzzy input. Example: "If temperature is high, then fan speed should be fast [4]." These rules are defined using linguistic variables and can be derived from expert knowledge. Fuzzy Inference System (FIS) This is the process of formulating the mapping from a given input to an output using fuzzy logic [5]. It involves Fuzzification: Converting crisp inputs into degrees of membership for fuzzy sets. Rule Evaluation: Applying fuzzy rules to the fuzzified inputs to produce a fuzzy output [6]. Aggregation of Outputs: Combining the outputs of all rules. Defuzzification: Converting the fuzzy output back into a crisp value. Types of Fuzzy Inference Systems Mamdani FIS: Uses fuzzy sets for both the input and output and requires defuzzification. Sugeno FIS: Uses fuzzy sets for inputs but outputs are typically linear functions of the inputs or constant values, simplifying defuzzification [7]. Practical Example: Fuzzy Logic in Control Systems Consider a simple fuzzy logic controller for a room heating system: Define Input and Output Variables:

Input: Temperature (cold, warm, hot), Output: Heater Power (low, medium, high)

Define and create Membership Functions

Temperature: "cold" (0-15°C), "warm" (10-25°C), "hot" (20-35°C), Heater Power: "low" (0-50%), "medium" (30-70%), "high" (60-100%).temperature is cold, then the heater power is high. temperature is warm, then the heater power is medium. temperature is hot, then the heater power is low. Applying the rules to determine the fuzzy output for a given input temperature. Convert the fuzzy output to a crisp heater power setting [8]. The advantages of Fuzzy Logic are as follows: Flexibility: Can handle imprecise information. Simplicity: Easy to understand and implement. Robustness: Tolerant of uncertain or approximate data [9].

Applications of Fuzzy Logic Control Systems: HVAC systems, washing machines, automotive systems. Decision Making: Risk assessment, financial systems. Pattern Recognition: Image processing, speech recognition [10]. Understanding and implementing fuzzy logic requires familiarity with fuzzy set theory, the ability to define membership functions and the skills to create and apply fuzzy rules. By modelling complex systems with approximate reasoning, fuzzy logic provides a powerful tool for dealing with uncertainty and imprecision in various real-world applications. Fuzzy logic provides a way to handle the uncertainty and imprecision often present in risk assessment. It can be used effectively to calculate decision-making in risk assessment by evaluating various risk factors and their associated uncertainties [11]. Here’s a step-by-step guide to how you can calculate decision-making for risk assessment using fuzzy logic: Define Risk Factors and Their Linguistic Variables by Identifying the key risk factors involved in the assessment. These could be things like Likelihood of a threat (e.g., Low, Medium, High)

Impact of the threat (e.g., Low, Medium, High), Vulnerability (e.g., Low, Medium, High)

Control effectiveness (e.g., Poor, Average, Good)

Membership Functions for each linguistic variable, define membership functions. Membership functions map the crisp values (actual measurements) to fuzzy values (degree of belonging to a linguistic variable). Common types of membership functions include triangular, trapezoidal, and Gaussian.

For example, for the risk factor "Likelihood of a threat":

Low: Triangular membership function with a peak at 0.2 and spread from 0 to 0.4.

Medium: Triangular membership function with a peak at 0.5 and spread from 0.3 to 0.7.

High: Triangular membership function with a peak at 0.8 and spread from 0.6 to 1.0.

Fuzzification - Convert the crisp values of risk factors into fuzzy values using the defined membership functions. This process is called fuzzification.

For instance, if the likelihood of a threat is measured at 0.6:

Low: μLow(0.6) = 0, Medium: μMedium(0.6) = 0.67, High: μHigh(0.6) = 0.33

Fuzzy Rules - Establish a set of fuzzy rules that relate the input variables to the output variable. These rules are often based on expert knowledge.

IF Likelihood is High AND Impact is High THEN Risk is High

IF Likelihood is Medium AND Impact is Medium THEN Risk is Medium

IF Likelihood is Low AND Impact is Low THEN Risk is Low

Inference - To generate fuzzy outputs, apply the fuzzy rules to the fuzzified inputs. Use methods like the Mamdani inference method to combine the rules and obtain the fuzzy output. The Mamdani inference method is one of the most widely used fuzzy inference techniques. It involves several steps: fuzzification, rule evaluation, aggregation, and defuzzification. Here's a detailed process on how to apply the Mamdani inference method to combine the rules and obtain the fuzzy output:

1. Fuzzification: Convert the crisp input values into fuzzy values using the membership functions defined for each input variable. For example, if we take sample data as

Likelihood (L) = 0.6

Impact (I) = 0.8

Membership functions for Likelihood:

Low: μL(x)mu_{L}(x)μL(x)

Medium: μM(x)mu_{M}(x)μM(x)

High: μH(x)mu_{H}(x)μH(x)

Membership functions for Impact:

Low: μL(x)mu_{L}(x)μL(x)

Medium: μM(x)mu_{M}(x)μM(x)

High: μH(x)mu_{H}(x)μH(x)

Fuzzification results:

μL,Low(0.6)=0mu_{L,text{Low}}(0.6) = 0μL,Low(0.6)=0

μL,Medium(0.6)=0.67mu_{L,text{Medium}}(0.6) = 0.67μL,Medium(0.6)=0.67

μL,High(0.6)=0.33mu_{L,text{High}}(0.6) = 0.33μL,High(0.6)=0.33

μI,Low(0.8)=0mu_{I,text{Low}}(0.8) = 0μI,Low(0.8)=0

μI,Medium(0.8)=0.33mu_{I,text{Medium}}(0.8) = 0.33μI,Medium(0.8)=0.33

μI,High(0.8)=0.67mu_{I,text{High}}(0.8) = 0.67μI,High(0.8)=0.67

2. Rule Evaluation

Evaluate the rules using the fuzzified inputs. The rules are in the form of IF-THEN statements.

Example rules:

IF Likelihood is High AND Impact is High THEN Risk is High

IF Likelihood is Medium AND Impact is Medium THEN Risk is Medium

IF Likelihood is Low AND Impact is Low THEN Risk is Low

For each rule, compute the degree of fulfilment (DOF) by taking the minimum of the antecedent memberships (AND operator).

Rule 1: DOF=min(μL,High(0.6),μI,High(0.8))=min(0.33,0.67)=0.33text{DOF} = min(mu_{L,text{High}}(0.6), mu_{I,text{High}}(0.8)) = min(0.33, 0.67) = 0.33DOF=min(μL,High(0.6),μI,High(0.8))=min(0.33,0.67)=0.33

Rule 2: DOF=min(μL,Medium(0.6),μI,Medium(0.8))=min(0.67,0.33)=0.33text{DOF} =min(mu_{L,text{Medium}}(0.6), mu_{I,text{Medium}}(0.8)) = min(0.67, 0.33) = 0.33DOF=min(μL,Medium(0.6),μI,Medium(0.8))=min(0.67,0.33)=0.33

Rule 3: Not applicable as both inputs do not fuzzify to Low.

3. Aggregation of Rule Outputs: Combine the outputs of all rules to form a single fuzzy set. This involves taking the maximum of the fuzzy outputs from each rule.

Membership functions for Risk:

Low: μRisk,Low(x)mu_{text{Risk,Low}}(x)μRisk,Low(x)

Medium: μRisk,Medium(x)mu_{text{Risk,Medium}}(x)μRisk,Medium(x)

High: μRisk,High(x)mu_{text{Risk,High}}(x)μRisk,High(x)

Rule outputs:

Rule 1 contributes to μRisk,Highmu_{text{Risk,High}}μRisk,High

Rule 2 contributes to μRisk,Mediummu_{text{Risk,Medium}}μRisk,Medium

Aggregate the contributions: μRisk, Aggregate(x)=max(μRisk,High(x)∩0.33, μRisk,Medium(x)∩0.33)mu_{text{Risk,Aggregate}}(x) = max(mu_{text{Risk,High}}(x) cap 0.33, mu_{text{Risk,Medium}}(x) cap 0.33)μRisk,Aggregate(x)=max(μRisk,High (x)∩0.33,μRisk,Medium(x)∩0.33)

4. Defuzzification

Convert the aggregated fuzzy set into a crisp value. The centroid (centre of gravity) method is commonly used for this purpose.

Risk=∫x·μRisk,Aggregate(x) dx∫μRisk,Aggregate(x) dxtext{Risk} = frac{int x cdot mu_{text{Risk,Aggregate}}(x) , dx}{int mu_{text{Risk,Aggregate}}(x), dx}Risk=∫μRisk,Aggregate(x)dx∫x·μRisk,Aggregate(x)dx

Implementation of Triangular membership function: A simplified example using triangular membership functions for illustration.

Membership Functions:

μRisk,Low(x)mu_{text{Risk,Low}}(x)μRisk,Low(x) = Triangular(0, 0, 0.5)

μRisk,Medium(x)mu_{text{Risk,Medium}}(x)μRisk,Medium(x) = Triangular(0.3, 0.5, 0.7)

μRisk,High(x)mu_{text{Risk,High}}(x)μRisk,High(x) = Triangular(0.5, 1, 1)

Rule Contributions:

Rule 1: μRisk,High(x)∩0.33mu_{text{Risk,High}}(x) cap 0.33μRisk,High(x)∩0.33

Rule 2: μRisk,Medium(x)∩0.33mu_{text{Risk,Medium}}(x) cap 0.33μRisk,Medium (x)∩0.33

Aggregated Membership Function:

μRisk, Aggregate(x)=max(min(μRisk,High(x),0.33),min(μRisk,Medium(x),0.33))mu_{text{Risk,Aggregate}}(x) = max(min(mu_{text{Risk,High}}(x), 0.33), min(mu_{text{Risk,Medium}}(x), 0.33))μRisk,Aggregate(x)=max(min(μRisk,High (x),0.33),min(μRisk,Medium(x),0.33))

Defuzzification: Calculate the centroid of the aggregated membership function:

$$x^* = \frac{\sum_{i=1}^{n} x_i \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)}$$

This will provide a crisp value representing the risk assessment. The Mamdani inference method offers a structured way to combine fuzzy rules and obtain a fuzzy output, which is then defuzzified to get a crisp risk value. This process handles the uncertainties and complexities inherent in risk assessment, making it a powerful tool for decision-making. Aggregation - Combine the fuzzy outputs from all the rules to form a single fuzzy set. This step typically involves taking the union (maximum) of all fuzzy sets representing the rule outputs. Defuzzification - Convert the aggregated fuzzy output back into a crisp value. Common defuzzification methods include the Centroid method (centre of gravity) and the Max membership principle. Example: Assume we have two risk factors: Likelihood (L) and Impact (I). Let’s use triangular membership functions for simplicity.

Membership Functions

Likelihood:

Low: (mu_L(x) = max(0, min((0.4-x)0.4, 1))),

Medium: (mu_M(x) = max(0, min((x-0.3)/0.2, (0.7-x)/0.2)))

High: (mu_H(x) = max(0, min((x-0.6)0.4, 1)))

Impact:

Low: Similar functions as Likelihood

Medium: Similar functions as Likelihood

High: Similar functions as Likelihood

Fuzzification

The example value assigned for Fuzzification is L:0.6 and I:0.8 as follows

L = 0.6

I = 0.8

Fuzzified values:

(mu_L(0.6) = 0), (mu_M(0.6) = 0.67), (mu_H(0.6) = 0.33)

(mu_L(0.8) = 0),(mu_M(0.8) = 0.33), (mu_H(0.8) = 0.67)

Rules

IF L is High AND I is High THEN Risk is High

IF L is Medium AND I is Medium THEN Risk is Medium

IF L is Low AND I is Low THEN Risk is Low

Inference and Aggregation

Rule 1: (min(mu_H(0.6), mu_H(0.8)) = min(0.33, 0.67) = 0.33)

Rule 2: (min(mu_M(0.6), mu_M(0.8)) = min(0.67, 0.33) = 0.33)

Rule 3: Not applicable as both inputs do not fuzzify to Low.

Defuzzification

Assume the output risk membership functions:

Low: (mu_{Low}(x))

Medium: (mu_{Med}(x))

High: (mu_{High}(x))

Using the Centroid method:

[text{Risk} = frac{int x cdot mu(x) , dx}{int mu(x) , dx}]

Where (mu(x)) is the aggregated membership function combining the outputs of all rules.

The centroid method would involve calculating the centre of the area under the curve defined by (mu_{Risk}(x)).

The Mamdani inference method is explained in a table format with some example data

Input variables: Likelihood (L) and Impact (I)

Output variable: Risk

Membership functions for each variable In fuzzy logic, membership functions (MFs) are mathematical functions that define how each point in the input space is mapped to a degree of membership between 0 and 1. These functions represent fuzzy sets and are used to transform crisp inputs into fuzzy values during the fuzzification process. The shape of the membership function can significantly affect the performance of a fuzzy system.

Fuzzy rules -Membership Functions

Table 1: Likelihood (L), Impact (I), and Risk:

Value	Low	Medium	High
0	1	0	0
0.2	0.8	0.2	0
0.4	0.4	0.6	0
0.6	0	0.67	0.33
0.8	0	0.33	0.67
1	0	0	1

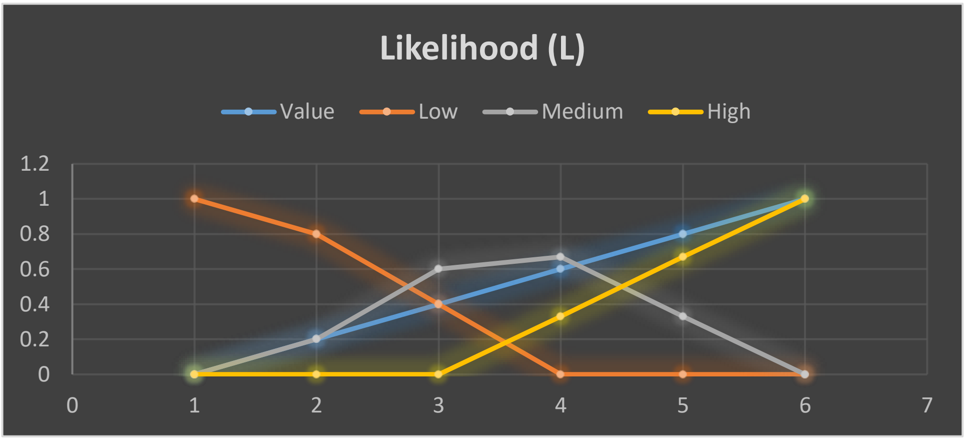

Figure 1: The membership values Chart

Table 1 and Figure 1 represent the membership values of different fuzzy sets (Low, Medium, High) for the variable Likelihood (L). Each row corresponds to a specific value of Likelihood (ranging from 0.0 to 1.0), and the columns indicate the degree to which that value belongs to each fuzzy set.

The table indicates how the likelihood values transition between the fuzzy sets Low, Medium, and High. At each step (from 0.0 to 1.0), the degrees of membership in each fuzzy set change, reflecting how the concept of Likelihood gradually shifts from being Low to Medium to High. This is a typical representation in fuzzy logic systems, allowing for gradual transitions rather than abrupt changes, capturing the inherent uncertainty and vagueness in real-world scenarios.

Fuzzification: Assume

Likelihood (L) = 0.6 , Impact (I) = 0.8

Table 2: Fuzzification:

Table: Membership Values for Inputs L and I			
Input	**Low**	**Medium**	**High**
L = 0.6	0	0.67	0.33
I = 0.8	0	0.33	0.67

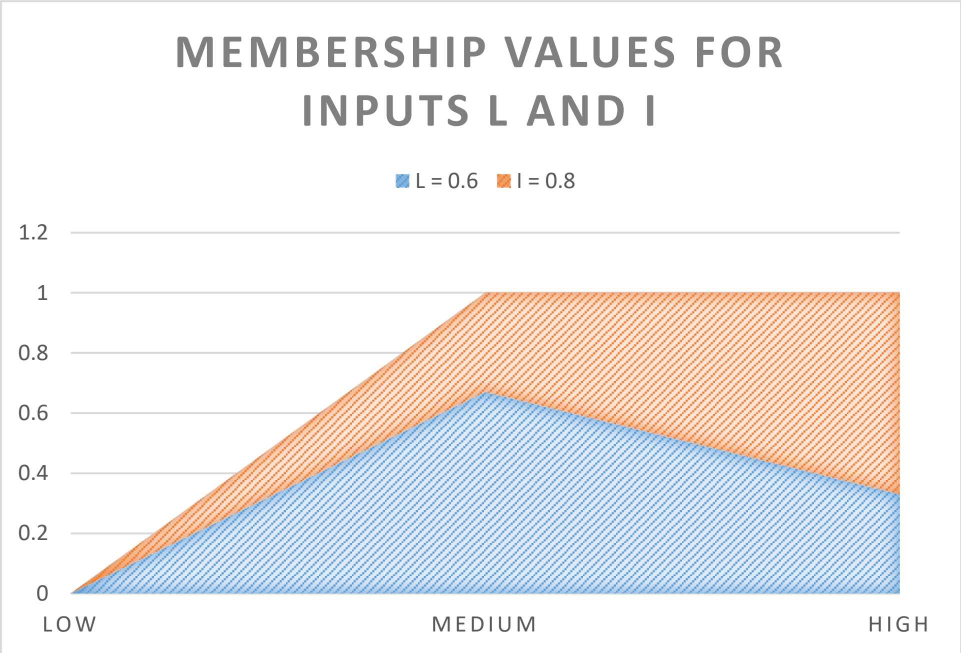

Figure 2: The degrees of membership

This table 2and Fig 2 shows how the inputs L and I, each with a value of 0.6 and 0.8 respectively, map to the degrees of membership in the fuzzy sets "Low," "Medium," and "High.". Input L (Likelihood) at 0.6 : **Low**: 0.00 (No membership in the Low fuzzy set), **Medium**: 0.67 (Moderate to high membership in the Medium fuzzy set) ,**High**: 0.33 (Moderate membership in the High fuzzy set). At L = 0.6, the value is predominantly in the Medium fuzzy set with a significant presence in the High fuzzy set but no presence in the Low fuzzy set. Input I (Intensity) at 0.8: **Low**: 0.00 (No membership in the Low fuzzy set), **Medium**: 0.33 (Low membership in the Medium fuzzy set), **High**: 0.67 (High membership in the High fuzzy set).

At I = 0.8, the value is mostly in the High fuzzy set with some presence in the Medium fuzzy set but no presence in the Low fuzzy set. The table above provides a clear view of how the inputs L and I, with values of 0.6 and 0.8 respectively, distribute their memberships across the fuzzy sets "Low," "Medium," and "High." This representation helps in understanding the fuzzy logic process where inputs are not just true or false but have degrees of belonging to multiple categories simultaneously.

Rule Evaluation

1. IF Likelihood is High AND Impact is High THEN Risk is High
2. IF Likelihood is Medium AND Impact is Medium THEN Risk is Medium
3. IF Likelihood is Low AND Impact is Low THEN Risk is Low

Table 3: Rule Evaluation:

Rule	**Likelihood (L)**	**Impact (I)**	**Min (AND)**	**Resultant Risk**
1	0.33 (High)	0.67 (High)	0.33	0.33 (High)
2	0.67 (Medium)	0.33 (Medium)	0.33	0.33 (Medium)
3	0 (Low)	0 (Low)	0	N/A

This table 3 illustrates how fuzzy logic rules can be applied to determine the resultant risk based on the given values of Likelihood and Impact. The resultant risk is derived using the minimum value of the memberships of Likelihood and Impact for each rule.

This process highlights how fuzzy logic manages uncertainty by allowing partial memberships across different fuzzy sets.

Step 3: Aggregation of Rule Outputs Combine the results of all rules:

Table 4: variable's values

Value	Low	Medium	High
0	0	0	0
0.2	0	0.2	0
0.4	0	0.33	0
0.6	0	0.33	0.33
0.8	0	0.33	0.33
1	0	0	0.33

This table 4 illustrates how a variable's values from 0.0 to 1.0 have different degrees of membership in the fuzzy sets "Low," "Medium," and "High."

The membership values indicate the extent to which each value belongs to these fuzzy sets, capturing the gradual transitions and overlapping nature typical of fuzzy logic systems.

Step 4: Defuzzification - Using the Centroid method to defuzzify:

$$x^* = \frac{\sum_{i=1}^{n} x_i \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)}$$

Table 5: Approximate the defuzzification process

Table: Aggregate Membership Values	
Value	**Membership (Aggregate)**
0	0
0.2	0.2
0.4	0.33
0.6	0.33
0.8	0.33
1	0.33

Approximated Centroid calculation: To calculate the approximate centroid (or centre of gravity) for the given Risk values using the provided formula, follow these steps:

Formula: The centroid calculation formula for the Risk is:

$$Risk=\sum Membership / \sum(Value\times Membership)$$

Given Values:

Values: 0.2, 0.4, 0.6, 0.8, 1.0

Memberships: 0.2, 0.33, 0.33, 0.33, 0.33

Numerator Calculation: $0.2\times0.2+0.4\times0.33+0.6\times0.33+0.8\times0.33+1.0\times0.33$

Breaking it down:

$0.2\times0.2=0.4$

$0.4\times0.33=0.132$

$0.6\times0.33=0.198$

$0.8\times0.33=0.264$

$1.0\times0.33=0.33$

Adding these products:

$0.04+0.132+0.198+0.264+0.33=0.9640.04$

Denominator Calculation:

$0.2+0.33+0.33+0.33+0.33=1.520.2$

Centroid Calculation:

$Risk=0.964/1.52\approx0.634$

Final Result: The approximate centroid for the given Risk values is:

Risk≈0.634

This calculation shows that the fuzzy risk assessment's centre of gravity (or centroid) is approximately 0.634. The calculated Risk value is approximately 0.634. The above table format example provides a clear and structured way to illustrate the Mamdani inference method in fuzzy logic for risk assessment.

Conclusion:

In conclusion, fuzzy logic provides a robust framework for converting subjective risk assessments into a structured and quantifiable decision-making process. By fuzzifying inputs, applying fuzzy rules, aggregating results, and defuzzifying outputs, it effectively manages uncertainty and imprecision. The Mamdani inference method, in particular, enhances this process by offering a systematic way to combine fuzzy rules and generate precise risk values. Overall, the ability of fuzzy logic to handle the complexities and uncertainties inherent in risk assessment makes it an invaluable tool for informed and reliable decision-making.

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