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Fuzzy System Applied to Search for Feedback on Governance in The Province of Namibe

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Abstract

This project aims to develop a mathematical model based on fuzzy logic for mining citizens' opinions on governance in the Province of Namibe. Fuzzy logic, or fuzzy logic, an extension of Boolean logic, is especially effective in dealing with uncertainty and imprecision in opinions, allowing for a more accurate analysis of citizens' perceptions. The research involved collecting fifteen responses from citizens from the five municipalities of the province, all aged at least eighteen and with a secondary or higher education level. Preliminary results indicate an average government performance of 0.07 on a scale of -1 to 1, with the fisheries sector standing out positively (0.23) and the health (-0.06) and housing (0.02) sectors showing the worst performances. The proposed approach combines data mining with fuzzy logic, allowing for the assignment of degrees of relevance to opinions, which offers a solid basis for the formulation of more informed and effective public policies. The innovative project not only fills gaps in the existing literature, but also offers an advanced methodology for analyzing large volumes of opinion data in natural language (text), whereas classical models only look for binary results such as “0 or 1, belongs or does not belong, True or False” and in this way it would not be possible to evaluate the Government's performance, hence the combination of text mining with fuzzy logic (Nebulous).

1. Introduction

Opinion mining plays a very important role in advancing studies in the area of Artificial Intelligence (AI), specifically in the field of Natural Language Processing (NLP) and Machine Learning (ML). The increasing availability of unstructured data, such as comments on social networks, product reviews and citizen feedback on a given topic, offers a rich source of information about the opinions expressed by these people.

By applying opinion mining techniques, it is possible to extract valuable information from this data, which is essential to develop more intelligent and effective AI systems and models for solving problems, as is the specific case of the project under study in this research. Text mining is an area of Artificial intelligence, whose main objective is to extract implicit knowledge from large quantities of texts written in natural language. Its definition is quite similar to that given to data mining. Knowing the opinions of others is not only valid for individuals, but also for institutions (Pang & Lee, 2008).

In traditional data mining tasks, results are typically sought such as: true or false, exists or does not exist, 0 or 1, positive, neutral or negative, high or low, that is, traditional mining produces only binary results. As highlighted by Amaral (2016, p. 99), the combination of data mining with Fuzzy Logic allows the results to have degrees of pertinence, expressing the proximity of the elements in relation to the identified patterns and this makes Fuzzy mining useful in scenarios where information is vague, subjective or imprecise. In the present project, it was decided to combine the two approaches, in order to present a recent and innovative idea of dealing with vague, imprecise and ambiguous information.

2. Artificial Intelligence

As discussed (Cunha, 1912), in 1936, at just 24 years old, Alan Turing proposed a theoretical model used to simulate any form of algorithmic computation, which became known as the "Turing Machine". The system would be fed by a large tape, on which instructions of just one character were written. The system could read one instruction at a time, processing them according to an algorithm of predetermined codes, moving the tape forward or backward.

According to the (FIA, 2023), during the Second World War, in 1940, British mathematician Alan Turing developed a machine that allowed the breaking of secret Nazi codes, generated by another machine, patented by Arthur Scherbius and known as Enigma . Ten years later, he introduced the world to the Turing Test, also known as the Imitation Game, created to check whether the computer is capable of imitating human thinking.

Artificial intelligence (AI), as discussed (Russell & Norvig., 1995) in "Artificial Intelligence: A Modern Approach", encompasses a vast spectrum of techniques and methodologies aimed at creating systems capable of imitating or replicating human cognitive functions. These functions include the ability to learn, reason, perceive, solve problems and interact with the environment and other agents. The central objective of AI is to develop machines capable of carrying out tasks in an autonomous, efficient and adaptable manner, in many cases surpassing human capabilities in certain areas.

2.1. Data Mining (KDD)

Data Mining, also known as Database Knowledge Discovery, focuses on computerized exploration of large amounts of data to discover interesting patterns among this data (Taulli, 2020). As the authors point out (Freitas & Freitas, 2023), it is important that the results of the Knowledge Discovery process in a Database are understandable to us humans, and especially to the end users of the process, who are generally people who make decisions in the organizations.

KDD is a Natural Language Processing technique that studies the extraction of knowledge from structured databases. In discovering knowledge in a database, several steps are considered, such as pre-processing, post-processing and data evaluation.

2.2. Text Mining (KDT)

Text Mining applies the same analytical functions as data mining, but for textual data. It can be seen as an extension of Data Mining as described in (Filho, 2004). In (Silge & Robinson, 2017), textual data encompasses a vast and rich source of information, even in a format that is difficult to extract in an automated way.

KDT is a Natural Language Processing (NLP) technique that allows the extraction of knowledge from textual data to identify trends and patterns involving a set of processes such as tokenization, Stopwords and stoplist identification, stemming lemmatization among others.

This project addresses the mining of opinions (in textual form), expressed by citizens in order to collect feedback from governance in the province of Namibe-Angola, to measure, through linguistic variables, the Government's performance in the dimensions of Benefits, Opportunities, Costs and Risks, BOCR, with the quantifiers extremely dissatisfied, quite dissatisfied, very dissatisfied, somewhat dissatisfied, Indifferent, somewhat satisfied, very satisfied, quite satisfied and extremely satisfied, transformed into numerical data from 0 to 100.

2.2.1. Challenges of Opinion Mining

There are several challenges encountered when carrying out an opinion process. Just imagine what you want to do: make the computer capable of interpreting a certain document, or the emotion contained in it. This is not an easy task even for human beings, since different views and opinions influence the way each person reads and understands a text.

- Below we can see some challenges of opinion mining that can be faced on the web according to the report by (Rodrigues, Vieira, Malagoli, & Timmermann, 2019):
- Texts with errors and syntactically poorly formed sentences (which is quite common on blogs and social networks) make it difficult to search and classify them;
- It is not trivial to distinguish whether a text is an opinion or a fact, and mainly to identify in a fact whether there are embedded opinions;
- Texts may contain sarcasm and irony, which are difficult to identify and can impact results;
- A text can reference more than one item of interest (you can mention iPhone and iPod for example) with different opinions about the items, which can confuse the classification;
- Using pronouns to reference items can make it difficult to identify sentences that mention the item of interest;

However, it is clear that traditional opinion mining methods are not as accurate to deal exactly with the challenges mentioned above, and the combination of this traditional method with Fuzzy Logic is an ideal option to deal with uncertainty and imprecision expressed by citizens. or entities responsible for the comments.

2.2.2. Opinion Mining Steps

Opinion mining is an essential process in the field of natural language processing, covering several steps to extract valuable information from textual data related to feelings and opinions. The figure below shows this process synthetically:

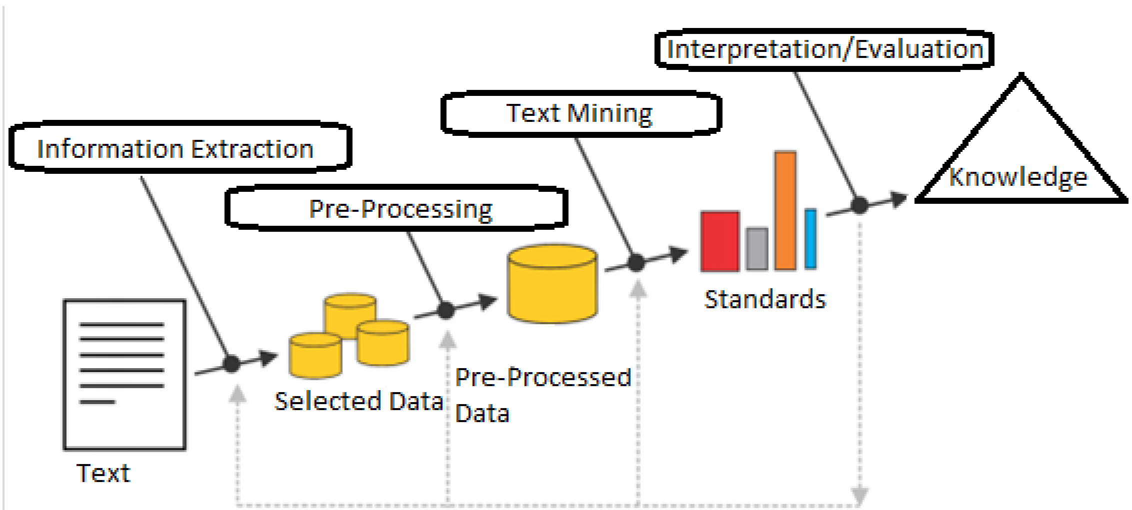


Figure 1 - Opinion mining steps, Adapted from (Michael, 2015)

3. Métricas de Avaliação de Desempenho

Performance evaluation metrics play a crucial role in data analysis and machine learning, as they provide an objective way to measure the performance of any model being created. They are essential for verifying that the results produced by models are accurate and useful when classifying data.

There are mathematical functions that help to measure the accuracy and error capacity of data models. In the approach taken by (Filho, 2004, p. 45), the following mathematical functions will be presented: Precision, Recall, F-measure and Accuracy, and for the present work the Accuracy and Precision metrics will be used to evaluate the model as discussed (Filho, 2004, p. 47):

- True Positives (TP): are the values classified as truly positive by the classifier;
- True Negatives (TN): these are negative instances that were correctly labeled by the classifier;
- False Positives (FP): false positives, data erroneously classified as positive by the classifier;

- False Negatives (FN): these are positive instances that were incorrectly classified as negative by the classifier;

Precision: is the value of the positive prediction (number of positive cases per total instances):

$$Precision = \frac{\text{TP}}{(TP + FP)}$$

And Recall is considered as a measure of completeness:

$$Recall = \frac{\text{TP}}{(FN + TP)}$$

Accuracy takes into account true and false positives and negatives and is generally considered a balanced measure that can be used even where classes are of very different sizes:

$$Acuracy = \frac{\text{TP} + \text{TN}}{(TP + TN + FP + FN)}$$

The F-measure is used to measure performance by combining precision and recall values into a single formula:

$$F - Measure = \frac{2 * \text{Recall} * \text{Precision}}{Recall + Precision}$$

The Misclassification Rate is a measure of the general error of the mathematical model. It is useful to do this calculation to evaluate the overall performance of the model in terms of misclassifications. The lower the Misclassification Rate, the better the model performs in making correct predictions:

$$Misclassification\ Rate = \frac{\text{FP} + \text{FN}}{TP + TN + FP + FN}$$

After this process, it is necessary to calculate the sum of the normalized metrics in order to be sure of finding 100% positivity between the real class and the predictive class (model), this time, the following formulas are used:

Normalized accuracy: Normalized accuracy takes into account the distribution of classes in the dataset.

$$Normalized\ Accuracy = \frac{Accuracy}{Accuracy +\ precision}$$

Normalized Accuracy: Normalized accuracy takes into account the accuracy of each class independently rather than treating all classes equally.

$$Normalized\ Precision = \frac{precision}{precision + Accuracy}$$

In general, the summations of the normalized metrics were successful when the value is equal to 1, otherwise the model must be adjusted with the completeness metrics Recall, F-meassure and Misclassification Rate if these apply. To do this, the following formula is used:

$$Normalized\ Sum =\ AccuracyNormalized\ +\ Normalized\ Precision$$

The base represents the sum of normal accuracy and normal precision.

4. Fuzzy Logic

Fuzzy Logic was first introduced in 1930 by the Polish philosopher and logician Jan Lukasiewicz. Through the study of terms such as high, old and hot, he proposed the use of a range of values [0,1] that would indicate the possibility that a statement was true or false.

In 1937, philosopher Max Black proposed the idea that continuity described degrees. He defined the first fuzzy set and described some basic ideals of fuzzy set operations. In 1965, Lofti Zadeh published the article

Fuzzy Sets, which became known as the origin of Fuzzy Logic. In reality, Zadeh rediscovered the idea of Fuzzy fication, identified and explored this concept, as well as fought for it.

A fuzzy set, or Fuzzy set, differs from a classical set by assigning each element a value in the unitary interval (0, 1). Specifically, a fuzzy set is defined as a function A from a set x, called the universe of discourse, for (0, 1).

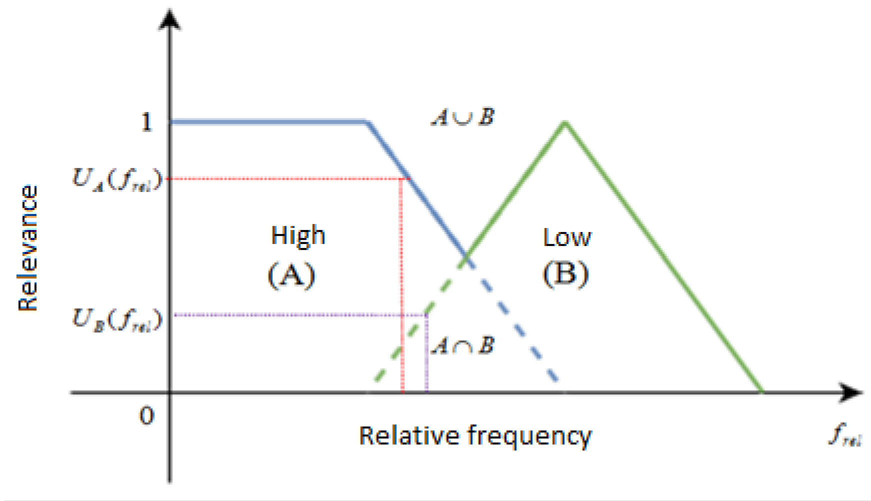


Figure 2 - Example of a fuzzy set, Source: Extracted from (Marro, Souza, Cavalcante, Bezerra, & Nunes, 2022)

4.1. Conventional logic x Fuzzy logic

Classical set theory allows the treatment of classes of objects and their interrelationships in a defined universe. In this theory, the membership of a given element in relation to a set refers to whether or not such an element belongs to that set.

To exemplify this logic, we will consider the example illustrated in figure 3, which represents a typical example of the classical theory and describes a person's height through three sets: low, medium and high. Where, given any element x, it will belong to one of the sets of the graph; for example, if x = 1.65, then x belongs to the average set and not to the others, that is, an element does or does not belong to a given set and, furthermore, the element itself does not belong to more than one set.

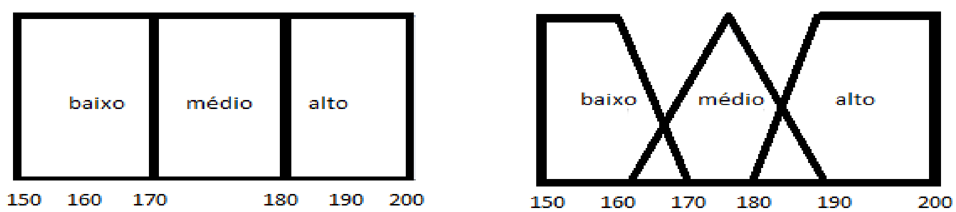


Figure 3 – Data representation in the form of sets, Source: Adapted from (Marro, Souza, Cavalcante, Bezerra, & Nunes, 2022)

Unlike conventional logic, Fuzzy Logic uses the idea that all things admit degrees of membership (temperature, height, speed). With this, Fuzzy Logic tries to model the human being's sense of words, decision making or common sense.

4.2. Fuzzy sets

In classical logic, sets are well defined, so that an element belongs to a set or not; if it belongs, it belongs to only one. This prevents ambiguities from appearing and makes the logic simpler. Still considering the example of using sets to separate people by height, a person measuring 1.69m would be considered a person of average height, if defined that way, being only in that set and in no other; Now, a person who is 1.71m tall would be part of the group of tall people, and only this group.

However, in reality, it is very difficult to see that people with such a minimal height difference belong to different groups. On the other hand, from the perspective of Fuzzy Logic, there would be two people with a certain degree of pertinence to the two sets, varying between 0 and 1, that is, we would have decision-making based on more human, more malleable factors. Thus, it can be concluded that the fuzzy sets that classify the elements of a given universe are less rigid than those used in classical theory since they admit partial degrees of membership.

$$f(x)= \begin{cases} 1 \text{ if and only if, } x \in A \\ 0 \text{ if and only if, } x \notin A \end{cases} \qquad (1)$$

$$\mu(x)= \begin{cases} 1 \text{ if and only if, } x \in A \\ 0 \text{ if and only if, } x \notin A \\ 0 \leq \boldsymbol{\mu}(x) \geq 1, \text{if x partially belongs to A} \end{cases} \qquad (2)$$

In this way, Fuzzy Logic can be considered as a set of mathematical principles for representing knowledge based on the degree of relevance of terms (degrees of truth). As can be seen in expression 2, the membership interval is [0,1], where 0 means that an element does not belong to a given set, 1 means complete membership to the set, and values between 0 and 1 represent partial degrees of membership.

Thus, in Fuzzy Logic, an element belongs to a set with a certain degree of membership, meaning that a given sentence can be partially true and partially false. Furthermore, the same element can have degrees of membership different from 0 to more than one fuzzy set.

4.3. Variáveis linguísticas e modificadores

A linguistic (or fuzzy) variable can be considered as an entity used to imprecisely represent – and, therefore, linguistically – a concept or variable of a given problem. A linguistic variable, unlike a numerical variable, only accepts values defined in the fuzzy language that is using it. For example: “Paulino_Alves is tall”.

The variable Paulino_Alves is receiving the high value, which is one of the fuzzy sets defined for this variable. Therefore, modifiers are terms or operations that modify the form of fuzzy sets (i.e., the intensity of fuzzy values), such as the adverbs very, little, extremely, almost, more or less, among others.

These can be classified as increasers, when they increase the area of membership of a fuzzy set, or, analogously, decreasers, when they decrease the area of membership of a fuzzy set.

4.4. Fuzzy rules

Fuzzy rules are normal rules used to correctly operate fuzzy sets, with the aim of obtaining consequents. To create such rules you need reasoning consistent with what you want to handle and obtain. To achieve this, this reasoning must be divided into two steps: (1) evaluate the antecedent of the rule and (2) apply the result to the consequent.

4.5. Fuzzy Inferences

Fuzzy inference models are mathematical approaches used in fuzzy systems to make decisions or predictions based on imprecise or uncertain information.

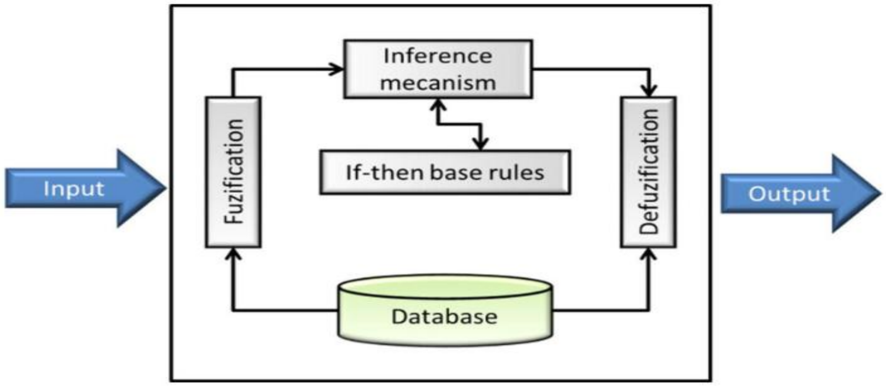


Figure 4 - Structure of the fuzzy inference system proposed by Mamdani and Assilian (1975)

According to (Marro, Souza, Cavalcante, Bezerra, & Nunes, 2022), there are several types of fuzzy inference models, including the TSK model (Takagi-Sugeno-Kang), Mamdani, Larsen, Sugeno, Wang-Mendel and others. Each model has its own characteristics, but generally, they involve the formulation of fuzzy rules that relate input variables to output variables.

For the present work, we chose Mamdani inference. The chosen method is widely accepted for capturing specialized knowledge, as is the specific case of seeking feedback on governance in the province of Namibe. It allows us to describe the experience in a more intuitive, more human-like way. However, the Mamdani type of inference implies a considerable computational burden.

5. Fuzzy Mining Steps

According to Ferrari (2016), Fuzzy mining follows the following steps:

- Text selection: Stage of searching, collecting and storing the data that will be analyzed. It is known in the literature as a corpus. It is also at this stage that the type of approach to be applied to the texts is defined: semantic or statistical, so that the next stage can be carried out;
- Pre-processing: The set of actions taken on textual documents in order to make them manipulable for the extraction of knowledge, considered the most important part of the process.
- Definition of Fuzzy Sets: At this stage, it is necessary to define the Fuzzy sets relevant to the variables involved in the problem. This includes determining linguistic terms and defining membership functions that describe the association of data values to these sets.
- Fuzzy Modeling: In this step, the pre-processed data is mapped to the previously defined Fuzzy sets. Each input value is associated with the appropriate Fuzzy sets using membership functions.
- Fuzzyfication: In this step, numerical values are converted into Fuzzy values, assigning them degrees of membership to the corresponding Fuzzy sets.
- Information mining: At this stage, once the selected texts have been transformed into structured data, we enter a stage in which the data becomes compatible for the use of Text Mining techniques. Thus, relevant parts of a text are searched for in a document and specific information is extracted. In other words, it is the stage in which text mining methods are applied.
- Analysis of results: This is the final stage with the objective of interpreting and analyzing the findings (evaluation of findings) obtained in the previous phase, a stage in which results validation techniques can be used to verify error rates and accuracy of the method.

6. Desenvolvimento do modelo

Given the S sets of services provided by the Provincial Government of Namibe, in the sectors $si \in S; i = \overline{1; N}$; and Q Given the S sets of services provided by the Provincial Government of Namibe, in the sectors si, how to mathematically infer the degree of satisfaction αki of the citizen $qk \in Q$;

$k = \overline{1; K}$?

For fuzzy mapping of the degree of satisfaction αki of the citizen qk, we use Thomas Saat's preference value scale, also called Fundamental Scale, illustrated in table 1.

Table 1 - Preference scale, adapted from Thomas Saat's fundamental scale

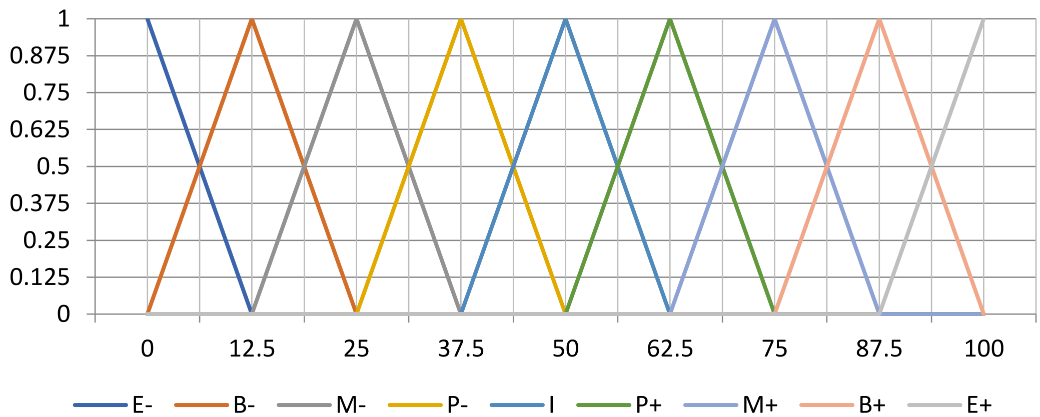
DISSATISFIED				INDIFFEREN T	SATISFIED			
Extremely	Quite	Very	Little		Little	Very	Quite	Extremely
E^-	B^-	M^-	P^-	I	P^+	M^+	B^+	E^+
0	**12,5**	**25**	**37,5**	**50**	**62,5**	**75**	**87,5**	**100**

Table 1 illustrates the distribution of possibilities in the field of defining citizen satisfaction through the linguistic variable Government performance.

Table 2 - Distribution of possibilities according to the preference scale (evaluation), adapted from Thomas Saat's fundamental scale.

	DISSATISFIED				INDIFFERENT	SATISFIED			
	E-	**B-**	**M-**	**P-**	**I**	**P+**	**M+**	**B+**	**E+**
bki	**0**	**12,5**	**25**	**37,5**	**50**	**62,5**	**75**	**87,5**	**100**
E-	1	0	0	0	0	0	0	0	0
B-	0	1	0	0	0	0	0	0	0
M-	0	0	1	0	0	0	0	0	0
P-	0	0	0	1	0	0	0	0	0
I	0	0	0	0	1	0	0	0	0
P+	0	0	0	0	0	1	0	0	0
M+	0	0	0	0	0	0	1	0	0
B+	0	0	0	0	0	0	0	1	0
E+	0	0	0	0	0	0	0	0	1

The graph below illustrates the distribution of possibilities in the field of defining citizen satisfaction.



Graphic 1 - Distribution of possibilities according to the preference scale (evaluation), adopted from Thomas Saaty's fundamental scale.

To infer the degree of citizen satisfaction, according to (Wapota, 2023), firstly, inference was made in the evaluation dimensions, which are Benefits (B), Opportunities (O), Costs (C) and Risks (R) to be carried out by the citizen in the Government service provision sectors:

- **Benefits**

Assessment of citizen q_k, regarding the Benefits $\tilde{b}_{ki}$ that the Government can offer in the $s_i \in S$, sector, is calculated by the following expression:

$$\tilde{b}_{ki} = max[\, \mu_{\tilde{B}^-}(b_{ki}).\, b_{ki};\, \mu_{\tilde{I}^-}(b_{ki}).\, b_{ki};\, \mu_{\tilde{B}^+}(b_{ki}).\, b_{ki}\,] \quad (1)$$

- **Opportunities**
- Assessment of citizen q_k, regarding the Opportunities $\tilde{o}_{ki}$ that the Government can offer in the $s_i \in S$, is calculated by the following expression:

$$\tilde{o}_{ki} = max[\, \mu_{\tilde{O}^-}(o_{ki}).\, o_{ki};\, \mu_{I}(o_{ki}).\, o_{ki};\, \mu_{\tilde{O}^+}(o_{ki}).\, o_{ki}\,] \quad (2)$$

- **Costs**

Assessment of citizen q_k, regarding the Costs $\tilde{c}_{ki}$ that the Government can offer in the $s_i \in S$, is calculated by the following expression:

$$\tilde{c}_{ki} = max[\, \mu_{\tilde{C}^-}(c_{ki}).\, c;\, \mu_{I}(c_{ki}).\, c_{ki};\, \mu_{\tilde{C}^+}(c_{ki}).\, c_{ki}\,] \quad (3)$$

- **Risks**

Assessment of citizen q_k, regarding the Risks r_{ki} that the Government can offer in the $s_i \in S$, is calculated by the following expression:

$$\tilde{r}_{ki} = max[\, \mu_{\tilde{R}^-}(r_{ki}).\, r_{ki};\, \mu_{I}(r_{ki}).\, r_{ki};\, \mu_{\tilde{R}^+}(r_{ki}).\, r_{ki}\,] \quad (4)$$

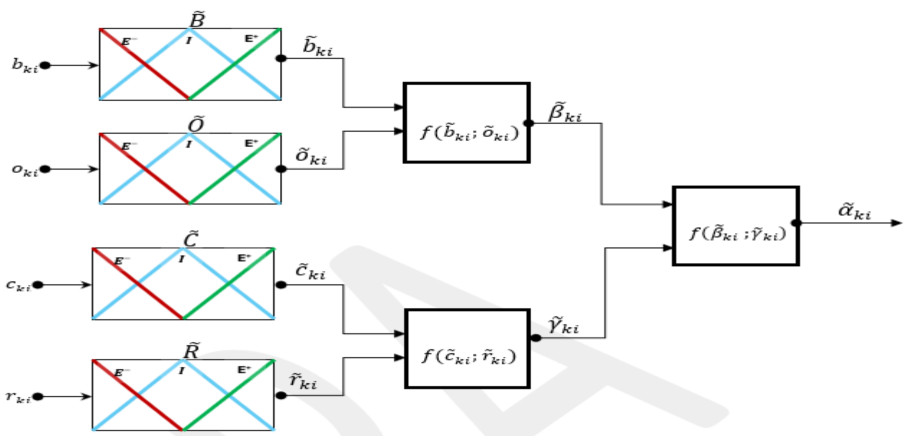


Figure 5 - Fuzzy inference scheme for the degree of citizen satisfaction qk regarding the governance of Namibe in the sectors si ∈ S.

Average rating by BOCR dimensions

$$\bar{B} = \frac{\sum_{k=1}^{K} \sum_{i=1}^{N} b_{ki}}{K*N}\ ; \quad (5)$$

$$\bar{O} = \frac{\sum_{k=1}^{K} \sum_{i=1}^{N} o_{ki}}{K*N},\ C = \frac{\sum_{k=1}^{K} \sum_{i=1}^{N} c_{ki}}{K*N}, \text{ e} \quad (6, 7)$$

$$\bar{R} = \frac{\sum_{k=1}^{K} \sum_{i=1}^{N} r_{ki}}{K*N} \quad (8)$$

6.1. Assessment of the total coherence of the Citizen's Assessment of the Services provided by the Government.

$$\tilde{\varphi} = \frac{\sum_{i=1}^{N} \sum_{k=1}^{K} \tilde{\varphi}_{ki}}{K*N} \quad (9)$$

Table 3 - Average Performance of the Provincial Government of Namibe by Sectors

Citizen K	Governance Sectors Si								
	Health	Education	Housing	Waters	Energy	Agriculture	Fisheries	Telecommunications	Public Works
1	0,09	0,11	0,2	0,3	0,11	0,11	0,22	0,22	0,2
2	0	-0,11	-0,11	0,11	0	0,11	0,11	-0,11	0,11
3	-0,14	-0,22	-0,3	-0,33	-0,67	-0,43	-0,44	-0,36	-0,43
4	0	0	0,2	-0,5	0	-0,11	0,43	0,09	0
5	-0,29	-0,08	1	0	0	0,18	-0,2	0,09	0,22
6	-0,62	-0,6	-1	-0,14	-0,17	0,29	0,2	-0,14	0,11
7	0	0,67	0	1	0,67	0,2	0,6	0,4	0
8	0,45	0,45	0,38	-0,43	0,05	0,15	0,38	-0,2	0,11
9	-0,11	-0,11	-0,11	-0,09	-0,09	0	0,14	0	0,11
10	-0,09	0,2	0	0,14	0	0	0,71	0	-0,28
11	0,11	0,11	-0,43	0,33	0,25	0,14	0,25	0,14	0
12	0,11	0,11	-0,43	0,33	0,25	0,14	0,25	0,14	0
13	-0,25	0,09	0,14	0,82	0,03	-0,11	0,25	0,25	0,11
14	-0,33	-0,09	0,25	0,25	0,33	0,25	0,25	0,25	0,11
15	0,11	0,16	0,45	0,25	0,25	0,25	0,25	0,25	0
Average Performance by Sector S_i, FzAlfa_ki	**-0,06**	**0,05**	**0,02**	**0,14**	**0,07**	**0,08**	**0,23**	**0,07**	**0,02**
Overall Average Performance, FzDg	**0,07**								

The Table above illustrates the average performance of each of the governance sectors, resulting from the compilation of the survey applied to 15 citizens represented by k and calculated using the function $\tilde{\alpha}_k$.

Table 3 - Fuzzy distribution (distribution of possibilities) of the Government's average performance by sectors

CLUSTERS	Performance Rating Terms	Performance SubCluster	Health	Education	Housing	Waters	Energy	Agriculture	Fisheries	Telecommunications	Public Works	Overall Average Performance, FzDg
BAD	Extremely Bad E-	-1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Pretty Bad B-	-0,75	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Very Bad M-	-0,5	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Little Bad P-	-0,25	0,26	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
INDIFFERENT	Indiferente(More or less) I	0	0,74	0,82	0,94	0,46	0,73	0,69	0,09	0,73	0,90	0,73
GOOD	Little Good P+	0,25	0,00	0,18	0,06	0,54	0,27	0,31	0,91	0,27	0,10	0,27
	Very Good M+	0,5	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Quite Good B+	0,75	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00
	Extremely Good E+	1	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00	0,00

The table above reveals a variety of citizens' perceptions about different sectors of governance, with some areas clearly in need of attention, such as Health, while others, such as Fisheries, are viewed more favorably. This analysis provides a solid basis for formulating policies that better meet the needs and perceptions of the population, aiming for a continuous and balanced improvement in the public services offered.

Table 4 - Average performance clusters of the Provincial Government of Namibe on the scale of -1 and 1

CLUSTERS	Performance Rating Terms	Performance SubCluster	Namibe Government Performance Cluster
BAD	Extremely Bad E-	-1	0,00
	Quite Bad B-	-0,75	0,00
	Very Bad M-	-0,5	0,00
	Little Bad P-	-0,25	0,00
INDIFFERENT	Indiferente(More or less) I	0	**0,72**
GOOD	Little Good P+	0,25	**0,28**
	Very Good M+	0,5	0,00
	Quite Good B+	0,75	0,00
	Extremely Good E+	1	0,00

The table above classifies the performance of the Provincial Government of Namibe into three main categories (Clusters): BAD, INDIFFERENT and GOOD, each subdivided into more specific terms ranging from -1 to 1. No negative evaluations were recorded, as all subclusters associated with negative performance (BAD) have values of 0.00. The majority of evaluations (72%) are concentrated in the Indifferent (More to Less) I category, which indicates a general neutral or indifferent perception of the government by the population. Only the subcluster Not very good P+ registered positive evaluations, corresponding to 28%, while the most positive categories (such as Very good, Fairly good and Extremely good) had no records.

7. Conclusion

The fuzzy mining model applied to the search for feedback on governance in the province of Namibe developed in the present project, demonstrated its effectiveness by offering a comprehensive and detailed analysis of the different governance sectors. One of its main advantages lies in its ability to deal with data uncertainty and imprecision, allowing a more accurate and refined assessment of the Namibe government's performance in various areas.

The results revealed that the fishing sector stands out as one of the best rated, with 0.23 (23%), followed by the water sector, with 0.14 (14%), indicating areas or sectors of significant improvement in governance. However, the worst sectors are particularly worrying is the health sector, which presented a value below 0, being -0.06 (-6%), suggesting an intervention in this area, followed by the housing and public works sectors, both with 0.2 (2%). From these results, one can infer the need for improvements in the provision of health services as well as housing and public works in the Province of Namibe.

All in all, considering the results obtained, the performance of the Government of Namibe on a scale of -1 to 1 is 0.07, belonging to the indifferent sub-coster or more at least with a degree of membership of 0.72 (72%), tending towards a good cluster, being in the subcluster Little more with a membership of 0.28 (28%). The results obtained were validated by the Government of Namibe and confirmed with the accuracy calculation to measure the precision and reliability of the proposed mathematical model, using the confusion matrix with the following metrics: Precision and Acuracy, where we found 70% model performance developed.

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