A Novel Approach to Evaluate the Quality of Life in Urban Environments by using Fuzzy classifiers

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Abstract

In this paper, we present our fuzzy classifier, built from scratch, and test how well it performs a task of classifying cities to either 'better' or 'worse' category, based on their numerical ratings of various aspects of living there. We check several combinations of norms and defuzzyfying methods, compare the results with three different fixed classifications - based on weighted sum, GDP per capita and human expert judgement. We also tried out few different classifiers, such as KNN, naive Bayes and soft set based classifier to see which one yields best results for this task.

Keywords

Fuzzy classifier, Teleport's city quality of life, Expert systems, Type 1 fuzzy sets

1. Introduction

The latest trends in the creation of modern IT systems are based on the use of artificial intelligence systems [1, 2]. A very important part of the application are solutions based on [3, 4, 5, 6, 7] neural networks. The use of neural networks is related to the protection of health [8], the detection of various, often not obvious for a human, features [9, 10, 11]. The use of neural networks in machine learning [12, 13] is also very popular. This work will be devoted to the applications of fuzzy sets [14, 15, 16] which have many different applications, including in car systems [17] or in computational intelligence [18, 19, 20] systems also applied to the field of smart home [21] and environment [22].

In this day and the age, due to modern technology and expansion of the Internet, people have access to much more data than ever before[23, 24, 25], which grants the possibility of greatly empowering their decision making processes. However, in the sheer amount and size of the available informations lies its biggest problem – it is unreasonable for single person to do as much research as it is necessesary for an informed decision. Solution to this problem appears in form of centralized and focused data sources, where information is easily available, grouped and distilled into its most relevant form for laymen, and recommendation systems, which aim to take the process step further, and directly asks users about their needs in order to compile list of best answers. It is this type of solution, which captured our interest. We created a classifier based on fuzzy logic, which takes in a vector with numerical ratings (scale from 0 to 1.0) of various attributes of the examined city and produces a numerical value from 1 to 100 alongside with linguistical value 'better' or 'worse', all based on comparison with expert knowledge database, written in form of if-then rules with chained linguistical values describing selected attributes of city's conditions. We conducted a range of tests to see the influence of different parameters, rulesets, datasets and other classifiers on effectiveness of this approach.

SYSYEM 2022: 8th Scholar's Yearly Symposium of Technology, Engineering and Mathematics, Brunek, July 23, 2022
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2. Overview

2.1. Introduction to fuzzy logic

The main idea between fuzzy logic is that there are some phenomena which are best interpreted by humans when they are described with words, not numbers, therefore some kind of system must exist in order to connect numerical data to linguistic terms, to then perform all the reasoning and at the end be able to convert the result back to number, if necessary. Because the process of reasoning, mostly referred to as inference, happens with the sole use of words, so linguistic values, it is managable for human experts to inject their reasoning into the system, even in vague terms, to reliably simulate intuitive and realistic judgements. For example, a fuzzy system gets some the measurement of the temperature, let's say 20°C, is able to translate it to linguisitc value "hot", it sees that expert defined behavior "if temperature is hot then don't use heating system" then concludes that there is no need for heater to be enabled, so it shuts it off.

2.2. Fuzzy logic flow

1. Preparations - expert defines rules for evaluation, and all the antecedents and consequents as well as their membership functions. Antecedents refer to categories of fuzzy variables, so the variables that have

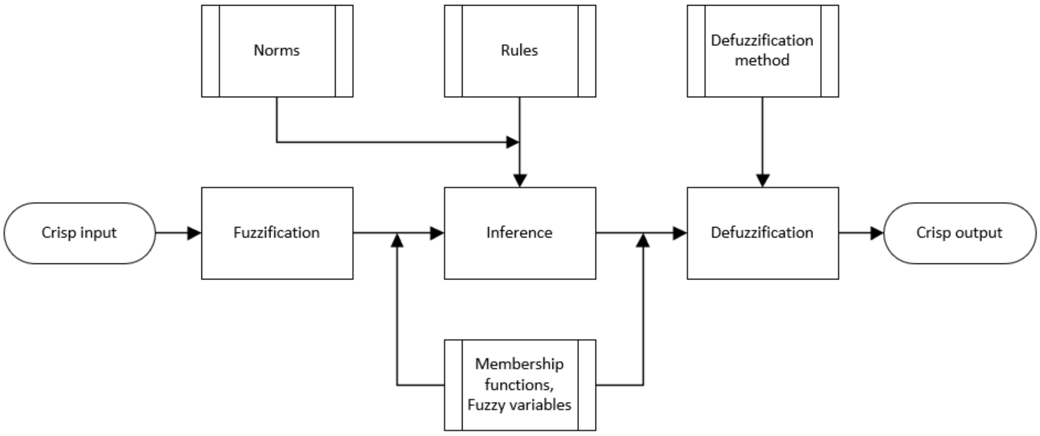

Figure 1: Flowchart of the fuzzy system

numerical and linguistical interpretations, for example ratings of Housing and Taxation. Consequents refer to potential outcomes from the system, for example Good, Average, Bad.

2. Input - numerical input, usually vector of numeric values, is provided. It will be referred to as "crisp value"

3. Fuzzification - crisp values from inputted vector are being used as arguments for each membership function of the linguistic category they refer to. Membership function with highest value from each category will define which linguistic value will be bound to corresponding attribute of the input vector.

4. Inference - numerical interpretations of degrees of membership from fuzzification step are being used in calculation of each rule's level of fulfilment. Evaluation process includes numerical interpretation of logical operations between rule requirements. For each possible linguistic value of an outcome its highest activated rule value, so a result of former evaluations, is being saved.

5. Defuzzification - a function is being made, by combining all the consequent membership functions and maximas of their corresponding rule activation results. Based on this function's set of values, given defuzzification method generates single numerical value. It is the outcome of the procedure.

   Flow of the fuzzy logic is presented in figure 1.

2.3. Membership functions

Degree of membership of each variable to a linguistic category is contained within a numerical value from range $[0, 1]$. It is a result of passing numerical value, in our implementation min-max normalized, to a predefined function of membership of its category. Fuzzy logic provides many versitale functions for such a process, with the most popular ones, and the ones used in our project, being triangular and trapezoidal.
Triangular:

$$\mu_{\text{trimf}}(x) = \begin{cases} 0, & \text{if } x \leq a \\ \dfrac{x-a}{b-a}, & \text{if } a < x \leq b \\ \dfrac{c-x}{c-b}, & \text{if } b < x \leq c \\ 0, & \text{if } x > c \end{cases} \tag{1}$$

Trapezoidal:

$$\mu_{\text{trapmf}}(x) = \begin{cases} 0, & \text{if } x \leq a \\ \dfrac{x-a}{b-a}, & \text{if } a < x \leq b \\ 1, & \text{if } b < x \leq c \\ \dfrac{d-x}{d-c}, & \text{if } c < x \leq d \\ 0, & \text{if } x > d \end{cases} \tag{2}$$

There exists a possibility of defining different types of membership functions for each linguistic value within a category (figure 2). It is sometimes a good practice to do such a thing, especially when operating on a few thin triangular functions, as there is a need to cover wide range of extreme values, which we want to guarantee to yield as a result (figure 3).

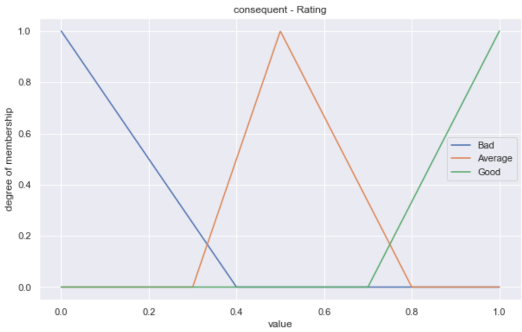

Figure 2: Consequent membership functions (triangulars)

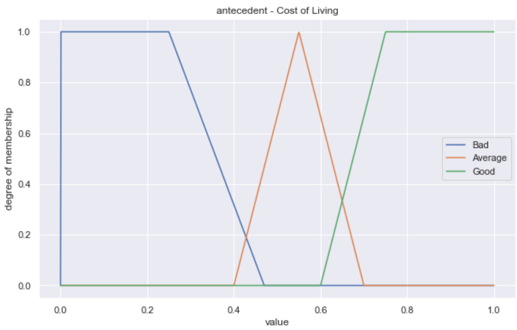

Figure 3: Housing antecedent membership functions (trapezoidal, triangular, trapezoidal)

2.4. Defuzzification methods

There are numberous defuzzification methods, which operate in very different ways. For our research, we were focusing on FOM (First Of Maxima), MOM (Middle Of Maxima), LOM (Last Of Maxima) and centroid middle of area. The first three return as their result the first, mean of or last occurance of highest activated function values, and the centroid one operates in a way described below:

$$\frac{\sum_{i=1}^{n} x_i \mu(x_i)}{\sum_{i=1}^{n} \mu(x_i)} \tag{3}$$

Visualization of an example output of center of areas defuzzification is presented in figure 4.

2.5. Norms

Norms refer to the different ways of numerically interpreting logical operations on linguistic values, such as

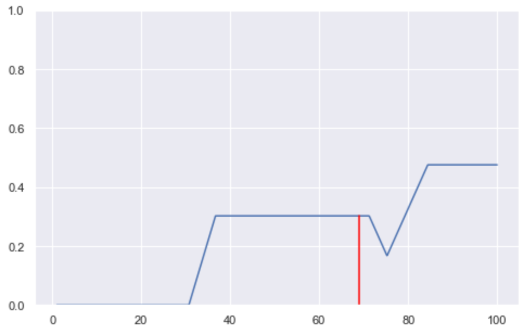

Figure 4: Center of areas

conjunction and alternative. We tested three different norms.

- Manger's Norm (Extended)
  - 'a & b' $\rightarrow a * b$
  - 'a | b' $\rightarrow a + b - a * b$
- Zadeh's Norm
  - 'a & b' $\rightarrow min(a, b)$
  - 'a | b' $\rightarrow max(a, b)$
- Łukasiewicz's Norm
  - 'a & b' $\rightarrow max(0, a + b - 1)$
  - 'a | b' $\rightarrow min(1, a + b)$

2.6. Rules

One of the stages of inference is usage of rules system. Single rule takes linguistic values of observation's attributes, processes them checking multiple conditions linked with themselves by mathematical logic and if all conditions are fulfilled, certain linguistic value that determines class is returned.
Our rules system is based on division of attributes on two main categories – important and less important ones. We assessed that some of observation's qualities are absolutely essential for every citizen (Housing, Cost of living, Safety, Healthcare, Travel connectivity) and some are not (Education, Environmental quality, Economy, Taxation, Internet access, Leisure and culture, Commute). For example healthcare is something that a lot of people are going to use in a critical situation that threathen them with death while education concerns only the younger citizens and culture is something that does not decide about survival and is additional bonus, not strategical factor. We created nine rules, where each three are built under the same pattern and the only varying element is linguistic value.

First rule states that any three among the five essential qualities, if their linguistic value is identical, determine returned linguistic value:

$$\textbf{If } (x_1 \textit{ is } a \textbf{ and } x_2 \textit{ is } a \textbf{ and } x_3 \textit{ is } a) \textbf{ or}$$
$$(x_1 \textit{ is } a \textbf{ and } x_2 \textit{ is } a \textbf{ and } x_4 \textit{ is } a) \textbf{ or } \ldots$$
$$\textbf{then } z \textit{ is } a$$

where $(x_1, x_2, x_3, x_4, x_5)$ are five essential qualities, $(y_1, y_2, y_3, y_4, y_5, y_6, y_7)$ are seven non-essential qualities, z is returned value and a is certain linguisitic value.
That rule contains all possible variations of three chosen attributes among the total five.
When four or five qualities have the same linguistic value, according to this logic that fact also determines returned value so it does not need to be handled by separate rule because it is intercepted by the first rule.
Second rule states that if two essential qualities have the same value, any two among the seven non-essential attributes with same value guarantee returned value equalled to theirs:

$$\textbf{If } ((x_1 \textit{ is } a \textbf{ and } x_2 \textit{ is } a) \textbf{ or } (x_2 \textit{ is } a \textbf{ and } x_3 \textit{ is } a) \textbf{ or } \ldots)$$
$$\textbf{and } ((y_1 \textit{ is } a \textbf{ and } y_2 \textit{ is } a) \textbf{ or } (y_2 \textit{ is } a \textbf{ and } y_3 \textit{ is } a) \textbf{ or } \ldots)$$
$$\textbf{then } z \textit{ is } a$$

That rule contains all variations of two attributes among the five and seven accordingly.
Third rule states that if only one essential quality have certain value, we need five non-essential attributes with this value to qualify returned value as identical to theirs:

$$\textbf{If } ((x_1 \textit{ is } a \textbf{ and } x_2 \textit{ is not } a \textbf{ and } x_3 \textit{ is not } a$$
$$\textbf{and } x_4 \textit{ is not } a \textbf{ and } x_5 \textit{ is not } a) \textbf{ or } \ldots) \textbf{ and}$$
$$((y_1 \textit{ is } a \textbf{ and } y_2 \textit{ is } a \textbf{ and } y_3 \textit{ is } a \textbf{ and } y_4 \textit{ is } a$$
$$\textbf{and } y_5 \textit{ is } a) \textbf{ or } \ldots)$$
$$\textbf{then } z \textit{ is } a$$

This rule contains all variations of one positive and four negative qualities among the five essential ones and five among seven non-essential ones.

3. Tests and experiments

To test our fuzzy system properly, we used three datasets, to which labels were assigned differently every time. Label of first dataset was created by constructing weighted sum of attributes where each quality did not contribute equally. Weight of the most of them was equal to 1, but some - more important to final decision in our opinion - were equal to 1.5 and one was equal to 0.5. Second dataset's label - GDP per capita - was obtained from external source. The last dataset's label was defined by authors by themselves and was based solely on their knowledge and intuition.
We checked results which were given by various combinations of norms (Zadeh norm, modified Manger norm, Łukasiewicz norm) with defuzzification methods (First of maxima, Last of maxima, Middle of maxima, centroid middle of area) applied within fuzzy system and a few other classifiers (KNN, Naïve Bayes, Softset). By results we mean four basic rates of model quality: accuracy, precision, recall and sensitivity. Except for accuracy, we decided to prioritize high scores of precision due to our attempts to achieve as little false positive cases as possible. The reason was that we did not want to propose a city as a potential proper location to live while it is not.
On all of the plots letter 'Z' denotes Zadeh norm, letter 'M' denotes modified Manger norm, letter 'L' denotes Łukasiewicz norm.
Results (figures 5 and 6) from the first dataset (weighted sum) show us a decent outcome from all of the different kinds of fuzzy system. They are very repetable and depend on used defuzzification methods, regardless of norms. Comparing it to the rest of classifiers, one may notice considerably lower performance of KNN, similar one of Softset and high result of Bayes.

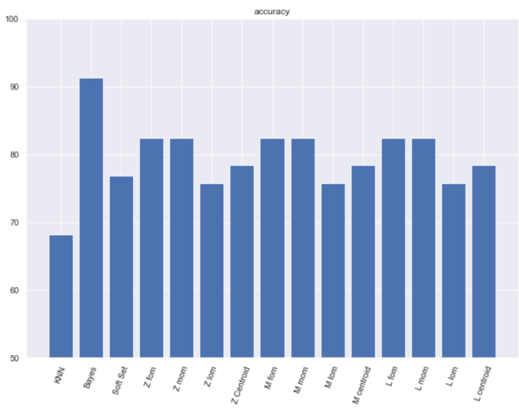

Figure 5: Accuracy rates for dataset with weighted sum

Second dataset (GDP per capita, figures 7 and 8) generated lower results of fuzzy system than that based on weighted sum. Again, individual cases are repetitive in similar way. This time KNN achieved better performance while Softset remains close to fuzzy outcomes. Bayes is still unmatched. All non-fuzzy models reached higher precision rates.

Third dataset (subjective classes, figures 9 and 10) produced similar outcomes to second one for fuzzy system - decent accuracy with poor precision. KNN and SoftSet have close results to themselves and Bayes as always

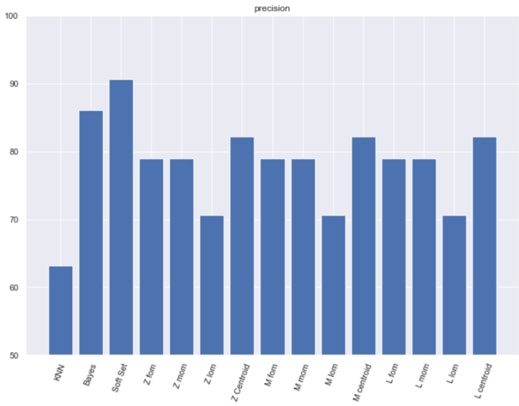

Figure 6: Precision rates for dataset with weighted sum

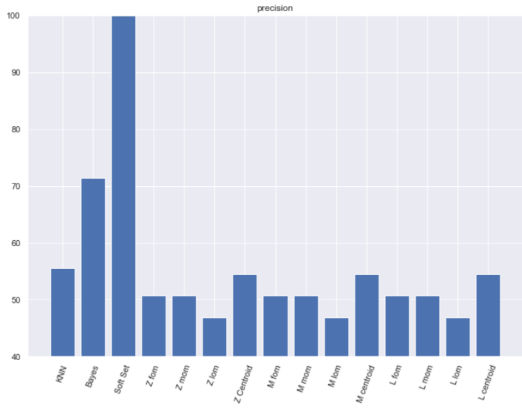

Figure 8: Precision rates for dataset with GDP

turned out to be the best model.

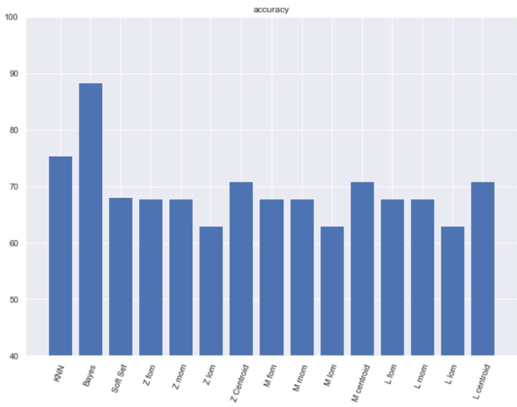

Figure 7: Accuracy rates for dataset with GDP

4. Conclusion

Fuzzy system achieved good results, especially using First of maxima and Middle of maxima defuzzification methods. Different norms were not a considerable factor, defuzzification pretty much defined the result by itself. The rest of the models reached mostly decent outcomes, sometimes even outperforming fuzzy system. Particularly Bayesian classifier turned out to have the highest score in nearly every case (considering accuracy and precision collectively). However, fuzzy system would likely achieve higher results in case of designing more accurate and factful system of rules by real expert or more adequate division into classes.

Although fuzzy system did not bring the best results from the bunch, we would argue that it provided good

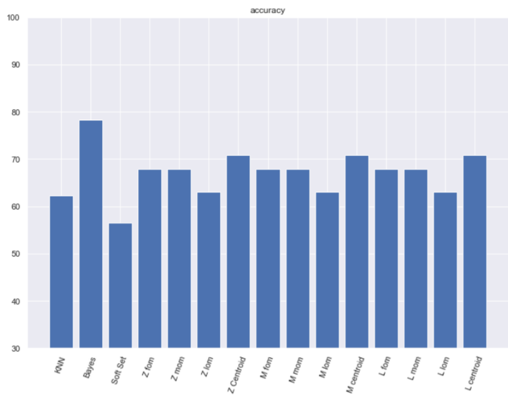

Figure 9: Accuracy rates for dataset with subjective classes

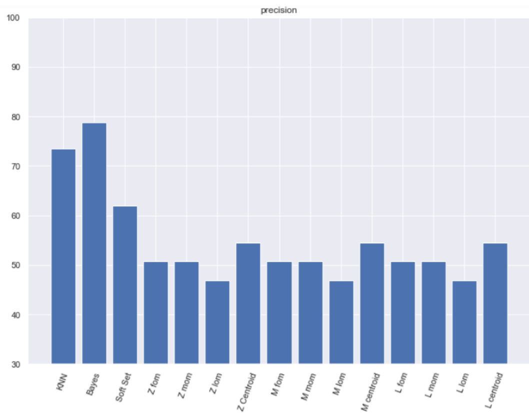

Figure 10: Precision rates for dataset with subjective classes

enough and consistent enough ratings to be used in any software, that would be able to capitalize on its strengths, such as flexibility of rulesets, enabling different user criteria, and no reliance on other data samples.

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