# Fuzzy Inference in the Analysis of Non-interval Data

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*Abstract:* - An inference engine using fuzzy logic is proposed for the analysis of Likert-type questionnaire. This method was used to understand and incorporate the imprecision of items in a questionnaire so that a single score that encompassed the different scales of the questionnaire could be created. A parent-rated questionnaire called the Parent Checklist of Peer Relationships (PCPR) was used as an example. A single Fuzzy Inference score was calculated that accounted for both prosocial and aggressive behaviors. This score was significantly correlated with the PCPR scale scores, suggesting that the Fuzzy Inference score is valid. The Fuzzy Inference score and the PCPR scores were correlated with independent measures of behaviors based on previous coders' behavioral ratings. The Fuzzy Inference score was considered to be a better correlate of the earlier behavioral scores because it yielded significant correlations whereas the PCPR score correlations appeared erratic.

*Key words*: - Qualitative analysis, Likert-type scales, Fuzzy logic, Fuzzy inference, Peer relations

## 1 Introduction

A common approach to quantifying and analyzing qualitative data collected by questionnaires is the use of semantic scales such as Likert-type scales. While there are several variations in these types of scales, typically they involve a statement referred to as the stem and a response arrangement where the respondent is asked to indicate on an ordinal range the extent of agreement or disagreement. The origin of these types of scales is attributed to Rensis Likert who published this technique in 1932. The data gathered typically are analyzed with statistical procedures, such as multivariate techniques, that are not designed for considering such semantic variables. The level of difficulty in questionnaire design increases as the questionnaire attempts to determine abstract concepts such as attitudes and perception, behavioral constructs, or social interactions [1]. Beyond the difficulty of determining the correct questions to reliably measure a concept, analysis of such data requires much greater understanding of complex statistical tools and techniques to measure complex interactions. The underlying problem is the assumption that the response evoked by the scale statement is continuous and linear and therefore can be subdivided into any number of infinitesimal and equal intervals. As was pointed out there is an optimal scaling and that the subjects cluster their responses near the ends [2]. That is, there is no more information obtained from a 1 – 4 range of scale than a 1 – 9 scale range. Framing error is yet another problem pointed out by researchers. [3] and [4],[5] have shown that the responses to the same statement can vary depending on whether it is stated as a positive (e.g., 90% chance of surviving an illness) or a negative (e.g., 10 % chance of dying from the illness). Other issues such as drift towards social acceptability of response and influence of the context and not the meaning of the question, detailed in [6], bring into question the validity of the data analysis. Special care must be given to design of the instrument and manipulation of data to account for these influencing elements. What is needed for analyses is a system of calculus able to better handle semantic scales and the vagueness that they contain. Unclear boundaries and non-linearity of data must be managed without an excessive cost for precise measurement and without sacrificing correct inference and understanding.

## 2 Problem Formulation

In this paper we are proposing an approach for analysis of data gathered by questionnaire using fuzzy inference system. A development tool is used to fuzzify the gathered data and specify the fuzzy rules delineating the relationships and dependencies. The fuzzy inference system is then utilized to generate an output. The output of the fuzzy system is then compared and correlated with output values obtained with traditional statistical analysis techniques. The proposed system resolves some of the issues with analyzing qualitative data with quantitative techniques and provides a better output amalgamating the underlying interactions of the construct.

The remainder of the paper is organized as follows. First implementation of the fuzzy inference system is discussed, followed by the results of the comparison of the finding. Finally, the discussion of the functionality of the approach in analysis of data in social science fields is presented

# 3 Method

In this paper, we report on the utilization of a fuzzy inference system as the means for analysis of a set of data collected with a Likert-type questionnaire. The data set consists of parental ratings of 10- to 14-year-old adolescents using a modified version of the Checklist of Peer Relationships (CPR). The original version is a list of 12 questions concerning the child's popularity with peers as well as the child's aggressive behaviors with peers. There are 3 scales: Social Competence (6 items; internal coefficient alpha = .50; Reactive Aggression (3 items; internal coefficient alpha = .69; and Proactive Aggression. A fourth scale made up of four additional items assesses Relational Aggression (4 items; internal coefficient alpha = .71. Items are rated on a 5-point Likert-type scale, with 1 = never true and 5 = almost always true. Parents of 128 children completed the questionnaire via mail.

The following questions were explored:

1. Does the fuzzy inference system improve data analysis of Likert-type questionnaires?

2. How can fuzzy inference improve data analysis of the Checklist of Peer Relationships?

3. How consistent is the output of the fuzzy inference with the output of traditional data analysis?

## 3.1 Data Analysis

The response to each statement in the checklist was mapped to a membership function as depicted in Figure 3. Matlab version 7.0.1 fuzzy module was used for the mapping. The responses were: 1 = Never, 2 = Rarely true, 3 = Sometimes true, 4 = Usually true, 5 = Always true.

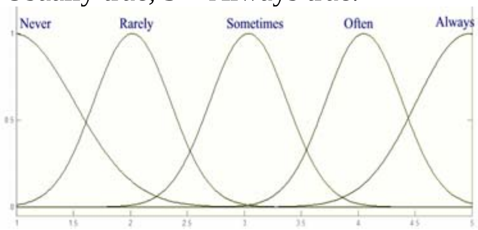


Figure 3. Membership function for the input values.

The choice of the membership function is somewhat arbitrary and is partially determined by the universe of discourse to be covered. We used a Gaussian membership function, as opposed to a Triangular membership function, because it was felt it best covers the gradual shift from one category to another and is best suited for the continuous variables [7].

A linguistic variable Peer Relationship Index (PRI) was created for the output with the following term set: Very Social, Friendly, Selfish, Aggressive, and Bullying. The graph of the membership function for the output is depicted in Figure 4. Again, a Gaussian membership function was utilized with the rationale that it best represents the concept.

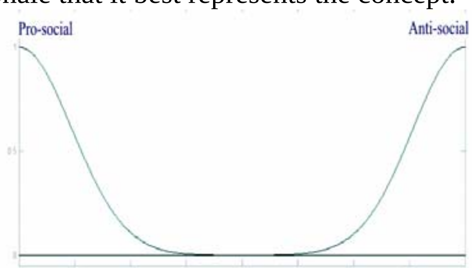


Figure 4. Membership function for the Peer Relation Index

Two rules derived from the four underlying constructs. The constructs were Social Competence, Reactive Aggression, Proactive Aggression, and Relational Aggression. The two rules group together all the pro-social questions and the aggression questions and evaluate the individual on this continuum.

MathLab was set to utilize the Mamdani inference method and the centroid defuzzification technique to convert the fuzzy input to an output for the Peer Relation Index. The centroid technique determines the defuzzified value by averaging the smallest value and the largest value of the output that have the highest membership value.

$$z = \frac{\max\{x\} + \min\{x\}}{2}, x \in M \qquad (1)$$

where $M$ is the set of output values with the highest membership value.

## 4 Results

The data from 128 subjects were fed to the inference engine constructed using the MatLab 7.0.1 fuzzy model. A set of scores ranging in value from the minimum of 1.26 to the maximum of 3.00 were obtained. The lower score indicates a more pro-social tendency. The results then were correlated with the results of the four subcategories typically obtained with the statistical analysis. Table 1 shows the Pearson correlation values based on all 128 participants.

Table 1
Correlation Coefficients Between the Fuzzy Inference Output and the Scores in Each Subcategory of the Checklist of Peer Relationships

| PCPR Scores | Fuzzy Inference output |
|---|---|
| Total aggression | .663 |
| Pro-Social | -.321 |
| Reactive | .564 |
| Proactive | .342 |
| Relational | .648 |

Note: All correlations are significant at $p < .001$.

Next, in order to determine whether the fuzzy model provided a better assessment of aggression and pro-social behaviors than did the originally scored instrument, both types of scores were correlated with behaviorally rated aggression and pro-social scores obtained when the children were 5 years old. The children had been observed and their behaviors were rated by trained coders rather than by parents in a peer play paradigm. 109 of the original 128 children were also tested at age 5. As can be seen in Table 2, the Fuzzy Inference score picks up on significant correlations that are erratic when viewing the PCPR scores.

Table 2
Correlation Coefficients Between the Fuzzy Inference Output and the Scores of Children's Play Behaviors at Age 5.

| Play Behavior Scores | Pro-social Time 1 | Pro-social Time 2 | Aggression Time 1 | Aggression Time 2 |
|---|---|---|---|---|
| F I output | .093 | 212* | .252** | 197* |
| CPR Total aggression | -.114 | -.200* | .227* | .112 |
| Pro-Social | .014 | .094 | -.171 | -.101 |
| Reactive Aggression | -.103 | -.216* | .184+ | .100 |
| Proactive Aggression | -.089 | -.144 | .263** | .101 |
| Relational Aggression | -.090 | -.127 | .158 | .082 |

+ $p < .06$, * $p < .05$, ** $p < .01$

Note: Time 1 represents children's play during the first 10 minutes of the peer play interaction. Time 2 represents children's play during the second 10 minutes of the interaction.
Thus, it appears to provide a more consistent picture of adolescent aggressive and pro-social behaviors as predicted by 5-year-old pro-social and aggressive play behaviors.

### 5 Discussion

A popular data gathering tool in the social sciences is a Likert-type scale questionnaire. Certain underlying assumptions that make analytical techniques robust may not be valid with data gathered by such questionnaires and may not provide adequate flexibility in the analysis. We have presented an alternative approach, namely fuzzy technique, which by design is more flexible and more tolerant of ambiguity. For the purpose of illustration, we developed a fuzzy inference system to analyze the data gathered with a checklist of peer relationships.

There are several comparative studies that look at the functionality and elasticity that fuzzy analysis brings to data analysis. [12] evaluated teacher activities with a Likert-type questionnaire and analyzed the data with both traditional methods and fuzzy technique. The authors concluded that "the fuzzy system could be a valid and reliable tool to represent situations described by qualitative ordinal variables…" (p 598). In comparing the fuzzy aggregation with numerical aggregation and cognitive aggregation, [9] reported that fuzzy set can effectively represent the vagueness of linguistic evaluations. In both cases, use of fuzzy analysis was reported to improve the modeling of complex human actions.

In our implementation, the data were fuzzified after collection on a crisp scale and the membership functions were determined based on those responses. However, if membership functions had been determined before data collection using a response scale that was more fluid and possibly had more gradations, the results might have been more differentiated. For instance, presently, the CPR has a range of responses between 1 (Never true) and 5 (Almost always true). The fuzzy inference system assigns a value to each response which is then aggregated and defuzzified to produce an output value. A finer semantic differentiation, that is, a greater range of responses between (Never true) to (Always true) might provide a better scoring scale. .

Our second question centered on how fuzzy inference can improve the data analysis of the Checklist of Peer Relationship. The out put of the CPR are four scores since there are 4 scales: Social Competence; Reactive Aggression; Proactive Aggression and Relational Aggression. Traditional analysis techniques are not adequately capable of accounting for contradictory and interacting factors. Therefore, a separate score is obtained for each subcategory. The interpretation of the multiple out puts is not as evocative as a single value that is reflective of all the influential factors. Fuzzy inference analysis through the execution of the fuzzy rules that were specified obtained a single value that is representative of all dominant factors. From this point of view, a major and significant problem in interpretation of data is resolved. Certainly, a single score that can represent all the interdependent factors is significantly more valuable than four separate scores, since the single score, provided it is reliable, can subsequently be utilized in constructing predictive models of the behavior.

Finally, the consistency of the fuzzy inference out put with traditional analysis was tested. A high degree of correlation was obtained between the fuzzy out put and the four subcategory scores. More interestingly, there was a more consistent relation between the fuzzy inference output score and the peer play behavior scores obtained at age 5 than there was between the adolescent CPR scores and the earlier play behavior scores. This is very promising since not only did the fuzzy inference result in a single value, as opposed to four scores with the traditional analysis, but also it seems to have more predictive capacity than traditional analysis.

It appears; therefore, that fuzzy inference design as an approach to analysis of Likert-type data has merit, especially with concepts with multiple constructs. In future work we intend to apply the technique to concepts that have more subcategories. For instance, the Behavioral Style Questionnaire (BSQ); [15] has nine sub-scales to evaluate nine temperament traits, but a single score combining information from each of the nine traits is not available. Therefore, if a fuzzy system can reduce this number to one reliable value, expert systems can be built around it for easier modeling of the behavior.

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