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Understanding Early Childhood Obesity Risks: An Empirical Study Using Fuzzy Signatures

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***Abstract*— Childhood obesity is a serious health problem that has adverse and long-lasting consequences for individuals, families, and communities. The magnitude of the problem has increased dramatically during the last three decades and, despite some indications of a plateau in this growth, the numbers remain stubbornly high. The nature of child obesity data is very complicated with different factors dependent on each other directly or indirectly affecting obesity as a whole. Traditional statistical analysis and machine learning approaches alone are not sufficient to model early childhood obesity risk and its impact on children's motor development. In this paper, we propose a computational model using Fuzzy Signature to understand and handle the intricacies of child obesity data and propose a solution that could be used to handle the risk associated with early childhood obesity and young children's motor development.**

I. Introduction

Childhood obesity is a serious health problem in the U.S. that can persist as children grow older and affect the quality and longevity of their adult lives [1]. Today, almost 10 percent of infants and toddlers carry excess weight for their length, and slightly more than 20 percent of children between the ages of two and five already are overweight or obese. A wide range of environmental factors can influence children's risk in the first years of life. Efforts to prevent childhood obesity have focused largely on school-aged children, with relatively little attention to children under age 5. However, there is a growing awareness that efforts to prevent childhood obesity must begin before children ever enter the school system.

The majority of childhood obesity research has been conducted in the medical realm, and thus has focused on biological and health determinants. However, it is important to consider other equally important effects of obesity on children's lives. In the early childhood years, children are experiencing rapid growth and development, and analysis of these data require advanced techniques that can account for these complex processes. Our aim is to capture the reality of the childhood obesity problem through the use of a computational model. This new approach, combining developmental and computer science techniques, could result in a deeper understanding of the intricacies inherent in early childhood obesity. Hence, in this paper, we are proposing an advanced approach to understand early childhood obesity risks using Fuzzy signatures [2].

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The fuzzy set framework has been used in several disease diagnosis processes, like obesity and diabetes [3], [4]. In most cases traditional machine learning or statistical [5], [6], [7] approaches have been used, and they require training data. So it is difficult to create a complex decision making system to analyze interdependent features existing in the data.

Obesity is a complex medical problem that can have numerous contributing factors. Medical practitioners tend to focus on the physiological aspect of obesity such as different blood composition level and basic metabolic index. However, there are also other factors, such as a home environment, family income, activity level, diet, and life habits, with different interdependent features that influence obesity. As a result it is very difficult to construct a complex a decision model to analyze these kinds of data. Fuzzy signatures are introduced to handle complex structures data with interdependent features. They can also be used in cases where data is missing. Our main aim is to formulate a model that would be capable of combining several such obesity risk factors and provide a value that would enable us to analyze a child's obesity risk.

Fuzzy logic is a computational paradigm that provides a mathematical tool for dealing with the uncertainty and the imprecision typical of human reasoning. Thus, fuzzy modeling has become very popular field in soft computing research because of its ability to assign meaningful linguistic labels to fuzzy sets in the rule base. Yet, it has its limitations when it comes to the high number of input variables, with complex and interdependent features. Fuzzy signatures are used to handle these scenarios.

Fuzzy signatures can be considered as special, multi-dimensional fuzzy data, where some of the components are interrelated in the sense that a subgroup of variables determines a feature on a higher level. This way, complex and interdependent data components can be described and evaluated in a compact way. The big advantage of fuzzy signatures is that they can deal with situations where some of the data components are not known.

The main *contributions* of this paper are as follows: (1) we are the first to propose a model analyzing early childhood obesity risk using fuzzy signatures; (2) we examine the influence of early childhood obesity risk on young children's motor development using the proposed approach.

The paper is organized as follows: section II discusses our proposed fuzzy signature framework for obesity risk analysis, section III analyzes how the fuzzy signature has been used to handle difference obesity risk factors with different case studies, section IV presents some related approaches that are relevant to this study, and finally section V concludes the paper.

II. Fuzzy Signature Framework for Obesity Risk Analysis

In this section, we construct a fuzzy signature to understand a child's obesity risk and its impact on motor development. In order to create the computational model, we introduce the preliminaries of fuzzy signature and then discuss different essential parameters that we have considered to create the fuzzy signature for our analysis.

A. Fuzzy Signature Preliminaries

Fuzzy signatures [2] are a generalized form of vector valued fuzzy sets [8], where each vector component is possibly another nested vector. This generalization can be continued recursively to any finite depth, thus forming a signature with depth m.

$$\begin{aligned} &A_s : x \to [a_i]_{i=1}^{k} \quad , \\ &a_i = \begin{cases} [0,1] \\ [a_{ij}]_{j=1}^{k_i} \end{cases} \quad , \\ &a_{ij} = \begin{cases} [0,1] \\ [a_{ijl}]_{l=1}^{k} \end{cases} \quad , \\ &\forall x \in X. \end{aligned} \tag{1}$$

The structure of fuzzy signatures can be represented both in vector form and also in a tree structure. Fuzzy signatures can be considered as special multi-dimensional fuzzy data [9]. Some of the dimensions are interrelated in the sense that they form sub-groups of variables, which jointly determine some feature on a higher level. Figure 1 shows an example of a fuzzy signature $x = [x_1\, x_2\, x_3]$. Here, $[x_{11}\, x_{12}]$ forms a subgroup that corresponds to a higher level compound variable of x_1. Then $[x_{221}\, x_{222}\, x_{223}]$ will combine together to form x_{22} and $[x_{21}[x_{221}\, x_{222}\, x_{223}]x_{23}]$ is equivalent on a higher level with $[x_{21}\, x_{22}\, x_{23}] = x_2$. Finally, the fuzzy signature structure will become $x = [x_1\, x_2\, x_3]$ in the example.

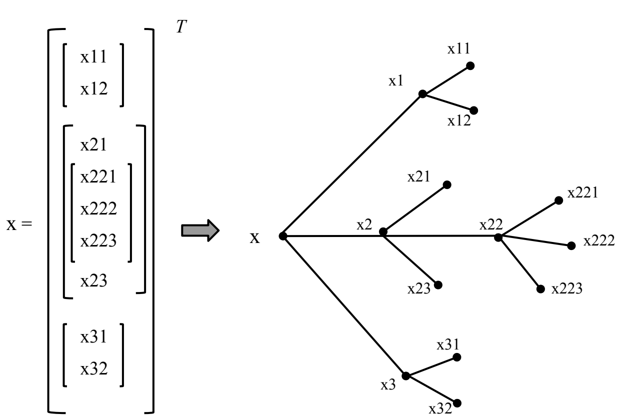

Fig. 1. Generic Fuzzy Signature

The relationship between higher and lower level is governed by a set of fuzzy aggregations. The results of the parent signature at each level are computed from their branches with appropriate aggregation of their child signatures. Let a_1 be the aggregation associating x_{11} and x_{12} used to derive x_1, thus $x_1 = x_{11} a_1 x_{12}$. By referring to Fig 1, the aggregations for the whole signature structure would be a_1, a_2, a_{22}, and a_3. These aggregations can be any of the simplest form, such as min, max or average.

B. Parameters for Child Obesity

Obesity can be due to various factors, which include family background, home environment, physical activity, and genetic composition. In this study, we focus on some of these factors. To analyze obesity risk in young children, we have focused on some important factors that relate directly and indirectly to children's development. Thus, our chosen parameters include three main obesity risk factors (also known as variables): family attributes, child activity, and home environment. These were selected based on previous studies examining child obesity, while also drawing on the larger body of social science developmental research.

1) *Family Attributes* include race/ethnicity, gender, and prematurity. Overweight affects children from non-White families disproportionately [10]. While specific links between gender, prematurity, and obesity have yet to be studied in young children, different patterns of influence for boys and girls have been discovered in school-age children [11]. Similarly, given the smaller birth weights associated with premature birth, and the resulting need for increased nutrition, it is logical to view prematurity as a risk to young children's height and weight.
2) *Child Activity* encompasses the space and equipment (materials) and scheduled time for gross motor activities, along with the frequency of activity. It is well understood that without materials or time, activity will not occur. In addition, how often the activity occurs relates to obesity risk, with more active children being less likely to be obese. With regard to physical activity, parent involvement remains significant, especially since children may not be getting the levels of physical activity they need while at preschool [12].
3) *Home Environment* includes the family's socioeconomic status (SES), which is a composite of income, occupation, and employment, and two specific habits related to obesity risk: diet and television viewing. Family income is recognized as a predictor of child overweight [13]. Household routines that decrease risk of overweight include eating meals as a family, limiting the time children spend watching television, and ensuring children get enough sleep each night [14]. A review of the literature regarding the relationship between child overweight and watching television further supports the contribution of interacting factors, as television viewing cannot stand alone as a risk factor of obesity in younger children [15].

Rationale for choosing the parameters: Since this is the first examination of early childhood obesity risk using fuzzy signature, we have opted to begin with a simplified model focusing on two parameters: child activity and home environment. This decision is based on the theoretical and empirical literature documenting (1) the relationship between physical activity and obesity risk, and (2) the significant impact of the home environment on young children's health and development. In addition, prior analysis by one author [16] structural equation modeling have demonstrated a direct and significant relationship between child activity and motor development (r=.465, p=.006).

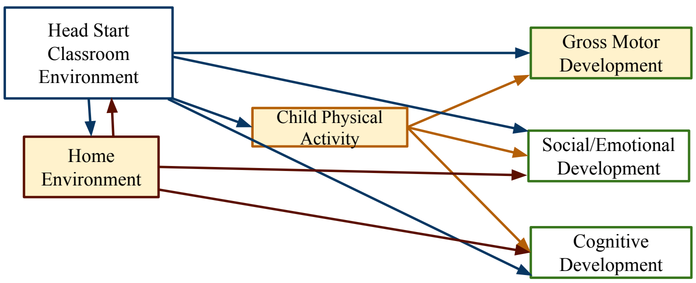

Fig. 2. Model of Early Childhood Obesity Risk (Shaded blocks are considered in this paper)

C. Construction of Fuzzy Signatures for Analyzing Early Childhood Obesity Risk

In sec II-B, different obesity risk factors (or parameters), have been explained. In this section, we use those parameters to construct our proposed fuzzy signature. Let O (as shown in Fig 3) represent the fuzzy signature. Based on expert comments in the area of child obesity, we have identified the interdependent parameters forming sub-groups in the fuzzy signature.

Child activity (or child's physical activity) and *home environment* are the two main risk factors, presented in the form of sub-groups of the fuzzy signature $O = [o_1\ o_2]$. Now, a child's overall physical activity is influenced by the *gross motor activity* and the *frequency of exercise*, forming the sub-group $[o_{11}\ o_{12}]$. Again, it has been observed that a child's gross motor activity is dependent on different resources or *materials* used for their development and the amount of time spend on motor activity (represented by *scheduled time*), and thus forming another sub-group $[o_{111}\ o_{112}]$ of o_{11}. We have further subdivided *materials*, o_{111} into *space for activity* and *equipment* available for a child's activities, forming another level of sub-groups $[o_{1111}\ \ o_{1112}]$ respectively. Thus, the whole signature (tree structure) of child activity o_1 can be represented as $[[[o_{1111}\ o_{1112}]\ o_{112}]\ o_{12}]$.

Based on the parameters we have selected, a child's home environment is another main factor influencing obesity, especially the family's socio-economic status and different habits practiced at home. Hence *socio-economic status* and *habits* have been primarily grouped under home environment, forming the sub-gropup $[o_{21}\ o_{22}]$. There are two main *habits*

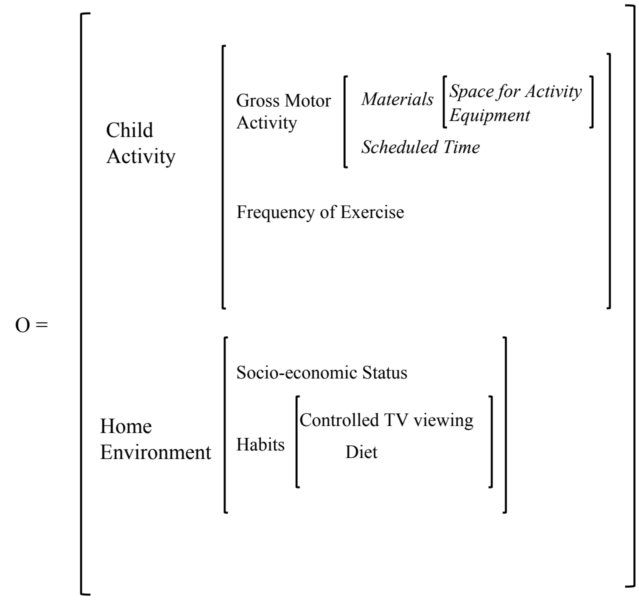

Fig. 3. Fuzzy Signature with Obesity Parameters

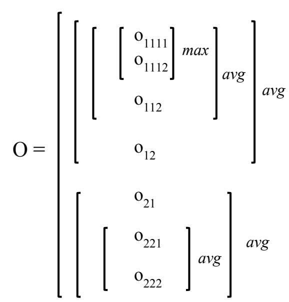

Fig. 4. Fuzzy Signature mapped with fig 3 with aggregations used at each level

that can affect children's health: diet and how much television (TV) is viewed (to be precise, this is how much parental control there is regarding children's TV viewing. If a child watches a large amount of TV, then activity, and therefore, motor development may be impacted negatively). Similarly, children's diets contribute to obesity risk. If children eat healthy food, then their overall development tends to be good. We can form a sub-group $[o_{221}\ \ o_{222}]$, which is equivalent to o_{22}. Hence, the home environment o_2 can finally be represented with all interdependent features in the form of $[o_{21}\ [o_{221}\ o_{222}]]$

As stated in sec II-A, the relationship between higher and lower level is governed by a set of fuzzy aggregations. The results of the parent signature at each level are computed from their branches with appropriate aggregation of their child signatures. We use avg to be the aggregation associating o_{1111} and o_{1111} to derive o_{111}, thus $o_{111} = o_{1111}\ avg\ o_{1112}$. By referring to Fig 4, the aggregations for the whole signature structure would be max, and avg at different levels.

According to [16], there is a direct significant relationship between child activity and motor development. Using the fuzzy signature, when we combine different parameters using relevant aggregations (as shown in Fig 4), we get an approximate value that can help us to better understand a child's obesity risk and how this risk relates to the child's motor development. This has been further deduced in sec III, where we present three different cases analysis and the results generated by our proposed fuzzy signature.

Mapping of linguistic labels with values: In Fig 5, a mapping of linguistic values with respect to crisp values shown. Based on human experts, we have determined the thresholds for each linguistic labels (shown in table I). The final aggregated value generated by the fuzzy signature has been further analyzed based on this mapping of a child's obesity risk and its impact on motor development.

TABLE I
MAPPING OF LINGUISTIC LABELS WITH VALUES

Linguistic label	Range of values
Low	$0 \leq x \leq 0.3$
Medium	$0.3 < x \leq 0.6$
High	$0.6 < x \leq 1$

$$O = \begin{bmatrix} \begin{bmatrix} \begin{bmatrix} \begin{bmatrix} \text{low} \\ \text{low} \end{bmatrix} \\ \text{medium} \end{bmatrix} \\ \text{low} \end{bmatrix} \\ \begin{bmatrix} \text{medium} \\ \begin{bmatrix} \text{low} \\ \text{low} \end{bmatrix} \end{bmatrix} \end{bmatrix} \Rightarrow \begin{bmatrix} \begin{bmatrix} \begin{bmatrix} \begin{bmatrix} 0.2 \\ 0.3 \end{bmatrix} \\ 0.5 \end{bmatrix} \\ 0.3 \end{bmatrix} \\ \begin{bmatrix} 0.5 \\ \begin{bmatrix} 0.3 \\ 0.3 \end{bmatrix} \end{bmatrix} \end{bmatrix}$$

Fig. 5. Linguistic Mapping of the Fuzzy Values from the Obesity Data

D. Obesity Risk Analysis and Motor Development

Investigations connecting obesity risk and early developmental outcomes are limited. Of note are two studies that highlight the relationship between obesity and two developmental areas gross motor and early regulatory skills, such as attention focus and behavior problems [17], [18]. Datar and colleagues [17], [19] have documented the negative influence of obesity on early academic achievement, while noting the influence of other child, family, and environmental factors. A more recent study supports the idea that intervention movement programs that encourage physical activity can actually improve development of motor skills and help fight environmental or genetic variables that may contribute to greater obesity risk in young children [20].

In this paper, we use fuzzy signature to combine multiple obesity risk factors and provide a unified value to represent a child's susceptibility to obesity risks. Based on different experts, it has been observed that the children who are healthy and less susceptible to obesity risks tend to have better motor development than children who are less healthy In other words, we can infer that obesity risk is inversely proportional to motor development (i.e., higher obesity risk results in lower motor development).

III. Case Studies

A. Nature of Data

Given our research focus, any data used for analysis should focus on young children from a variety of backgrounds and geographic locations in order to ensure it is reflective of the national population in the United States. It is essential that the data include measures of our three primary parameters, family attributes, child activity, and home environment, as described in section II-B. The data must also include sufficient participants from specific racial/ethnic and low-income backgrounds as they are known to be at higher risk for obesity. Specific variables will be selected based on their potential relation to the selected outcomes given extant theory and research.

TABLE II
DIFFERENT CASE STUDIES

Case	SA	E	ST	FE	SES	TV	D
I	0.2	0.3	0.4	0.3	0.2	0.2	0.3
II	0.2	0.3	0.5	0.3	0.5	0.3	0.3
III	0.7	0.5	0.8	0.4	0.9	0.4	0.8

Table II shows different values used for analyzing three main cases in figures 6, 7, and 8 respectively. The abbreviations of table II has been described in table III.

TABLE III
ABBREVIATIONS USED IN TABLE II

Abbreviations	Meaning
SA	Space for activity
E	Equipment
ST	Scheduled time
FE	Frequency of exercise
SES	Socio-economic status
TV	controlled TV viewing
D	Diet

B. Running Example Deducing the Outcome

In this section, we present some of the cases we have found while analyzing the early childhood obesity data. Three different scenarios are presented in the figures 6, 7, and 8 respectively. They all determine how fuzzy signature has been used to children's obesity risk and their motor development. The parametric values for each cases have been provided in table II.

Case I: Figure 6 explains the working steps of using our proposed fuzzy signature to combine different obesity risk factors using aggregations at each level. The values for each of the parameters are mostly low or nearing medium. After using the aggregations at each step in the fuzzy signature (as described in Fig 4), we finally get 0.27 from the fuzzy signature. This value gives us a two-fold perspective about child obesity. The *low* value (based on the threshold described in table I) signifies that the child is highly susceptible to obesity risk and at the same time it can also allow us to infer that the motor development of the child will be low (since obesity risk and motor development are inversely proportional usually).

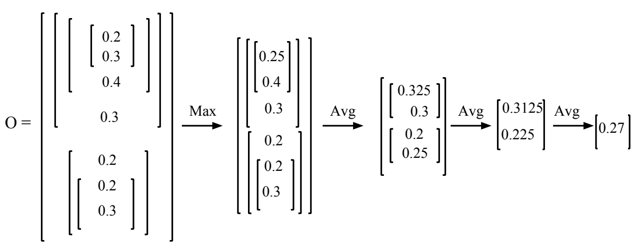

Fig. 6. Running Example - Case I

Case II: Like case I, Fig 7 also explains the working steps for combing the obesity risk parameters using case II values from table II. If we look at the values for this case, we find them raging from upper low to medium. Based on the aggregations shown in Fig 4, we finally obtained $0.375 \approx 0.4$, which falls in the *medium* range according to table I. From this value, it can be inferred that the child will have medium obesity risk and his motor development typical for his age will be medium.

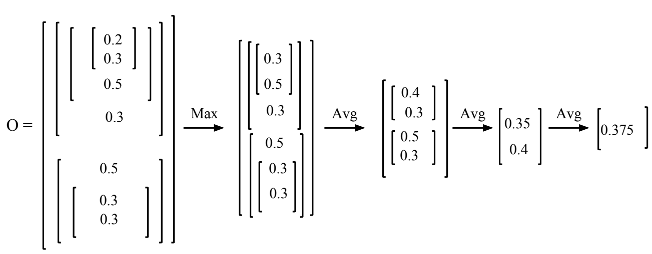

Fig. 7. Running Example - Case II

Case III: Like the previous two cases, if we look at the values of the parameters presented in table II, we would notice that the values in this case vary mostly from medium to high. Now, based on the aggregations, shown in Fig 4, we finally obtained 0.7 which falls in the group of high. Thus, we can infer that the child is free from obesity risk and will have a normal motor development.

Thus, from the above three cases, we have shown that our proposed fuzzy signature can give us an approximation of the combined parameters, which can help us to identify children's obesity risks and their motor development.

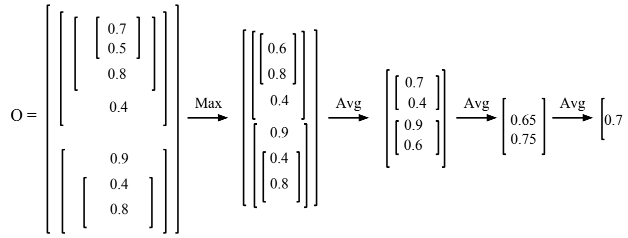

Fig. 8. Running Example - Case III

IV. Related Work

A. General Child Obesity and Risk

Overweight children are at risk for a multitude of health and social problems [21]. In terms of physical health, they have a greater risk of developing high cholesterol, type two diabetes, high blood pressure, and eating disorders. These diseases, often confined to middle aged adults, are now present in increasing numbers in young children. The negative effects of overweight may also present themselves in the social/emotional developmental realm. Overweight children may be last to be selected as playmates, for sports teams, or may be teased and ridiculed by peers. Over time the health effects coupled with more difficult social interactions may lead to lower self-esteem in overweight children [22]. There are also long-term consequences of overweight in early childhood, as increased body mass index (BMI) after age three predicts overweight in young adulthood [23].

While multiple risk factors for childhood obesity have been identified, including parenting practices, family income, television viewing, maternal BMI, and non-white racial and ethnic background [24], [25], [26], scant attention has been given to the mechanisms underlying children's obesity risk prior to school entry. The preschool period is an important time for children to develop the motor, cognitive, and social/emotional skills that will make them better prepared for kindergarten and later school success. However, investigations connecting obesity risk, home environments, and early developmental outcomes are limited [19], [27], [18].

B. Fuzzy Logic in medical informatics

There have been some studies in the computational intelligence area that deal with the analysis of different medical problems, such as obesity, diabetes, cancer. In this paper, we are primarily interested in the significant approaches using Fuzzy Logic and have been used in medical informatics.

Fuzzy set theory has a number of properties that make it suitable for formalizing the uncertain information upon which medical diagnosis and treatment is usually based. Firstly, it defines inexact medical entities as fuzzy sets. Secondly, it provides a linguistic approach with an excellent approximation to texts. Finally, fuzzy logic offers reasoning methods capable of drawing approximate inferences. In [28], [29], [30], [31], fuzzy logic has been a suggested method for the development of clinical decision support systems, due to its ability to deal with the uncertainty and vagueness of languages.

Fuzzy logic has also been used in the diagnosis of cancer. For example, in [32], [33], [34], [35], the authors have either used fuzzy logic or have combined with either evolutionary algorithms or neural networks to other machine learning algorithms to assist the medical practitioners.

In [3], Miyahira et. al., presented a fuzzy mechanism for evaluating obesity by associating BMI with Body Fat (BF) that yields a fuzzy obesity index for obesity evaluation and treatment and allows to build up a Fuzzy Decision Support System (FDSS) for bariatric surgery indication (BSI). Different values of Body Mass Index (BMI) and BF used for validating the proposed method classify individuals in distinct categories with degrees of compatibility more realistic than those accomplished by Boolean classification, as usually occur. There is limited use of fuzzy logic in relation to obesity but it has been applied more often in the area of diabetes to monitor and regulate blood glucose levels [36], [37], [38], [39], [40].

C. *Fuzzy Signatures and its Application*

Fuzzy signatures [2] has widely been applied to the fields that normally have objects with very complex and interdependent features. In [9], fuzzy signatures have been applied to aid in SARS pre-clinical diagnosis allowing medical practitioners to quickly classify patients as infected by SARS or ordinary flu virus. Fuzzy signatures have also been applied to other fields such as data mining [41], robotics [42], and pattern recognition [43].

V. Conclusion

In this paper, we have proposed a fuzzy signature framework to combine different parameters of early childhood obesity risk factors to determine young children's obesity risks and the impact on their motor development. Based on our analysis, we have shown that our model can provide us a meaningful approximation of the parameters and allow us to infer a justifiable outcome. In short, the present findings will assist prevention, intervention, and policy-related efforts to combat the obesity epidemic in young children.

Future work: We plan to extend our proposed model with weighted aggregations, because among all the obesity risk factors, some parameters have more dominant effects on obesity than others. So, it is essential to incorporate the feature of weighted aggregations into our fuzzy signature. We also want to use this approximated results for automatically classifying children's obesity risks.

Given our particular focus in this initial study, future investigations may expand the number of parameters related to the present outcome, motor development. It will also be informative to consider other aspects of young children's development, including cognitive and social/emotional development. In addition, examination of sub-groups based on family attributes known to increase obesity risk is important.

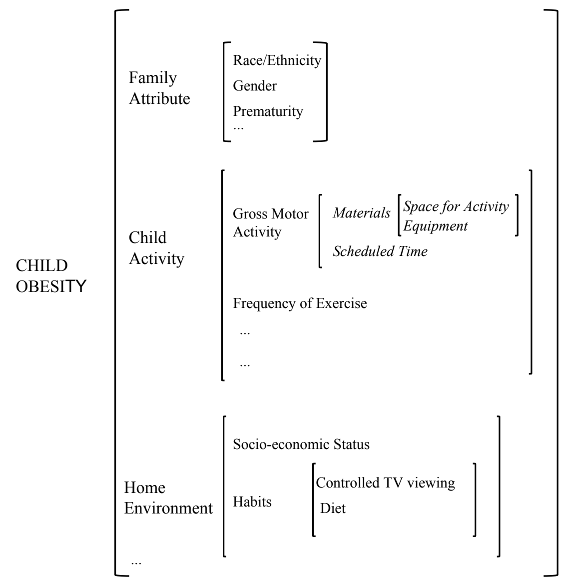

Fig. 9. Sample of Fuzzy Signature with more Parameters

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