An Artificial Agent to Recommend Activities to Minimize Childhood Obesity Problems in an IoT System

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Abstract. *Pediatric obesity is a recognized global epidemic. Its association with an increased risk of several future chronic diseases has been well documented. Among behavioral factors, both bad eating habits and sedentary lifestyle had been shown to be major determinants of obesity. This paper presents the first phase of the design process of an agent-based approach to recommend eating and physical activities to children, based on data collected from wearable devices and questionnaires filled by parents/teachers.*

Resumo. *A obesidade infantil representam uma reconhecida epidemia global. Sua associação com o aumento no risco futuro de várias doenças crônicas é amplamente conhecida. Entre os fatores comportamentais, tanto maus hábitos alimentares quanto o sedentarismo representam os principais determinantes da obesidade. Este artigo apresenta a primeira fase do processo de design de uma abordagem baseada em agentes para recomendar alimentos e atividades físicas para crianças, com base em dados coletados de dispositivos vestíveis e questionários preenchidos por pais/professores.*

1. Introduction

Childhood obesity has been considered a global epidemic by all renowned health organizations, one of the biggest medical problems of the 21st century. According to the World Health Organization, the number of school-age children and adolescents with obesity has risen from 11 million to 124 million in 2016, and the number of overweight children was estimated to be around 216 million in that year [NCD Risk Factor Collaboration 2017]. As alarming, the number of overweight or obese children in the world under the age of five was estimated to be over 38 million in 2017, increasing to over 70 million by 2025 if the current trend contin-ues [World Health Organization 2017, World Health Organization 2018]. From 1975 to 2016, the global prevalence of obesity in children and adolescents increased from 0.7% in girls to 5.6%, and from 0.9% to 7.8% in boys [NCD Risk Factor Collaboration 2017].

There is little lack of knowledge regarding the main biological drivers, causes and risk factors of obesity. Causes include, but are not limited to, unhealthy diet and eating habits, sedentary lifestyle, sleep deprivation, among other issues, including genetics and medical problems. Among behavioral factors, eating habits had been shown to be a major determinant of obesity [Kuźbicka and Rachoń 2013]. Research confirms the connection between sedentary lifestyle and obesity is strong [Boreham and Riddoch 2002]. Since those decisive sources of obesity are behavioral, attention must be directed to produce strategies to incorporate healthy habits in children, related to eating and physical activities. This paper describes the first phase of the design process of an agent-based approach to recommend personalized preventive and corrective actions to a child in an IoT system.

2. Agend-based Approach to Recommend Actions

The IoT system is a socio-technical system designed to assist children with obesity problems. By socio-technical, we mean a technical system that interacts with humans in an environment, trying to attain their goals. The technical system is composed of a hardware and a software part. The environment task is mainly composed by the children's home and school, the children and their parents, doctors and teachers. In this system, children are turned into a smart "thing" by wearing sensors that monitor their lifestyle.

From the Artificial Intelligence point of view, the system is as an organization of artificial and human agents interacting in a complex environment task. In this paper, we design and evaluate an agent program, for one of the artificial agent in the organization, named `Health_Advisor` agent, to to rationally select and recommend actions to a human agent, simulated in the design process by one other agent program named `Child`.

The recommendation problem was decomposed in two subproblems, that must be solved sequentially by the `Health_Advisor`. The Classification Problem, in which given a set of rules, based on some current attribute values, a child should be classified into a given class. The Monitoring Problem consists of a continuous recording of the states of the child and, given the solution of the classification problem and the child's desired state, sending messages to recommend preventive or corrective actions to be adopted.

2.1. Agent Programs' Abstract Architectures

The abstract architectures of our agent programs is described as an information processing system decomposed in three subsystems, represented by three functions: `see`, `next` and `action`. The scheme assumes that at any moment k, in a total time K:

1. through sensors, the `Health_Advisor` agent receives stimuli information about the `Child` agent, $s_H^k \in SH = \{s_{H1}, s_{H2}, ..., s_{Hn}\}$. That is, states defined on a set of n possible health states from `Child_Id`;
2. the perception subsystem, `seeA`: $S_H \rightarrow P_A$, processes the health state information $s_H^k \in S_H$ and maps it to one possible perception $p_A^k \in P_A = \{p_{A1}, p_{A2}, ...\}$, that are computational representations of aspects in the health state;
3. the internal state update subsystem, `nextA`: $P_A \times I_A \rightarrow I_A$, maps the current perception in $p_A^K \in P_A$ and the current internal state, $i_A^{k-1} \in I_A = i_{A1}, i_{A2}, \ldots$, to a new internal state $i_A^k \in I_A$, considering a model of the `Child` agent;
4. the decision-making subsystem, `actionA`: $I_A \rightarrow A_A$, processes the internal states $i_H^k \in I_H$ and selects an action in the set of possible actions for the agent, $a_A^k \in A_A = \{a_{H1}, a_{H2}, \ldots, a_{Hm}\}$, according to a set of condition-action rules;

5. through actuators, `Health_Advisor` recommends $a_A^k \in A_A$ to `Child`;
6. in interaction $k + 1$, the `Child` agent changes its current state $s_H^k \in S_H$ to a new state $s_H^{k+1} \in S_H$, according to the executed action $a_A^k \in A_A$, and the `Health_Advisor` agent initiates another cycle.

The internal state information $i_A^k \in I_A$ describes aspects of the environment that are not currently perceived by the Health Advisor agents sensors. Specifically, the `nextA` function must classify the child's health state, `Classify`: $P \rightarrow HealthClasses$. The condition-action rules consist of a set of common associations which are observed between certain conditions established from the descriptions of internal states in I and certain actions in A. Humans can feed these rules, they can be compiled from a deliberative process that considers the effect of actions in some states or be learned in different way.

At the other side, the `Child` agent computes the simulated child's new current state, to be sent to the `Health_Advisor` agent, considering the recommended actions, the previous state, and the information of a model of the child, i.e.: (a) the information about the effects of the execution of possible recommendation actions; (b) and the information about how the child's health states evolve in function of the moments in time $k \in K$, independently of the execution of any action.

The notion of desirability is captured by a performance measure, `performance`: $S_H \times A_A \rightarrow \mathbf{R}$, that maps a real number to every episode in the history of the interactions between the two agents in the environment, `history`: $(s_H^0, a_A^0)(s_H^1, a_A^1)\ldots(s_H^k, a_A^k)\ldots$, such that s_H^0 is the `Child` agent's initial health state, s_H^k is the health state in the beginning of the $k - th$ interaction, obtained with the execution of the recommendation action a_A^{k-1}, and a_A^k is the action that the `Health_Advisor` agent choose to recommend.

2.2. The Health Advisor Agent Program

The Health Advisor agent's skeleton must be adapted depending on the domain of possible values to attributes in X, defined by the set of attribute values to quantify P_A, i.e., the domain of stimuli, of health states, captured from the `Child`, and the solution space of the recommendation problem, defined by the set A_A of possible recommendation actions for the Health Advisor agent. Domain-specific information about the `ModelA` of the child, employed by the next subsystem `nextA`, and about `InfoDecisonA`, employed by the action subsystem `actionA`, are necessary to program the `Health_Advisor`.

The sensors for the `Health_Advisor` will include one or more video cameras, so that it can see the children's eating and physical habits, activity trackers, wireless-enabled wearable technology devices to measure the number of steps walked, heart rate, quality of sleep, and other personal metrics involved in fitness, and other information obtained by questionnaires. Among the various ways that the `Health_Advisor_Id` agent can represent the health states measured by the sensors, in this version we adopted a factored representation, splitting up each observed perception $p_A^k \in P_A$, the computational representation of health state $s_H^k \in S_H$, into a fixed set of N attributes, $X = \{x_1, x_2, \ldots, x_N\}$, and values in given domains, $p_A^k = (val_x 1^k, val_x 2^k, \ldots)$.

The actuators for the `Health_Advisor` include devices for sending recommendation actions to be displayed in a screen of a cellphone. Each recommendation action $a_A^k \in A_A$ can be represented in the form of an atomic message or of a sequence of messages defined in an alphabet of two fundamental messages, to request the children to take an action and to inform the children about a state in any time T: `request(Sender, Hearer, Action, T)` and `inform(Sender, Hearer, State, T)`.

In this version, we are considering that the information about `ModelA` and about `InfoDecisonA` are available in the problem domain as an expertise in the form of a set of heuristic rules (theories). Considering the perception $p_A^k = (val_x 1^k, val_x 2^k, \ldots)$ in the output of the `seeA` function and a set of three rules, suitable designed to compute the class of each current attribute value, the `nextA` function updates the agent's internal state with the information about the class of each attribute value, indicating its adequacy and the level of this adequacy. The rules were elaborated considering the existence of a fictional ruler, that must be defined for each attribute in the set X.

One ruler defined for an attribute $x_i \in X$ aggregates the information about a minimum value (Min_i) and about a maximum value (Max_i) for the x_i, defining the lower and the upper bound of its domain, an inferior margin value (Inf_i) and a superior margin value (Sup_i) in the domain, defining the range of values in the domain in which a current value val_{x1}^k will be classified as adequate. Optionally, depending on the attribute properties, the ruler can inform its ideal value ($Ideal_i$) in the range of adequate values.

Considering the information defining one specific ruler for an attribute x_i, rule $R2$ deals with the situation where the current value val_{xi}^k is adequate. Beyond the information about the adequacy class, the consequent of rule $R2$ informs the absolute value ($abs/1$) of the difference ($Diff/2$) between the ideal and the current value; and a severity level ($level_{xi}^k$) equal to 0 (zero), since the current value val_{xi}^k is in the range of adequate values and can be near the ideal value.

Rules $R1$ and $R3$ deal with the situation where the current value val_{xi}^k is inadequate. In rule $R1$, if the current value is greater than the superior margin value, it will be classified as inadequate and above, with a severity level $level_{xi}^k$ that is equal to the division of the difference between the current value and the superior margin value and the range length above ($above_i$) the superior value in the ruler. In this case, when val_{xi}^k is equal to Max_i, we have that the severity level $level_{xi}k$ is equal to 1 (one) and when val_{xi}^k is very near to Sup_i, we have that $level_{xi}^k$ is near to 0 (zero). Rule $R3$ will work symmetrically as $R1$, but when the current value is smaller than the inferior margin value.

After the `nextA` function has updated the agents internal state i_A^k, inserting the information about the perception p_A^k and about the classes of all current attribute values in p_A^k, the `actionA` function must select an recommendation action $a_A^k \in A_A$, based on a set of three condition-action rules, stated in the form of a single input and a single output rule, that must be applied to each attribute $x_i \in X$.

The consequent in the rules are defined employing three functions with specific arguments. The `preventive_rec` returns a suitable preventive recommendation action in the set $P = \{a_i^{p1}, a_i^{p2}, \ldots\}$, considering the $Difference$ in the health class information. The `corrective_rec_above` returns a suitable corrective recommendation action in the set $C_A = \{a_i^{ca1}, a_i^{ca2}, a_i^{ca3}, a_i^{ca4}, \ldots\}$ considering the above inadequacy class and the negative of the severity level $level_{xi}^k$. The `corrective_rec_bellow` returns a suitable corrective recommendation action in the set $C_B = \{a_i^{cb1}, a_i^{cb2}, a_i^{cb3}, a_i^{cb4}, a_i^{cb5}, \ldots\}$, considering the bellow inadequacy class and the severity level $level_{xi}^k$.

3. Experiments Design, Results and Analyses

This section presents initial results of the interactions of the two agents. In our architecture, the artificial agent named `Health_Advisor` interacts with an human agent simulated by an artificial agent named `Child`. The `Child` agent's skeleton must also be adapted depending on the domain of possible values to attributes in X and the solution space of the specific recommendation problem, defined by the set A_A of possible recommendation actions for the `Health_Advisor` agent. In the simulated scheme, in interaction $k+1$, the `Child` agent perceives the recommendation action, sent by the `Health_Advisor` agent. Considering this information and the information about the previous internal state, it generates a new internal state to be sent to the `Health_Advisor` agent.

To compute the new current state to be sent, two kinds of domain-specific information were considered by `Child`. The first one relates to how the child health states evolve from a previous moment k to the next known moment $k+1$ independently of the execution of any previous action in k. The second relates to the effect of the execution of possible recommendation actions in the last child health state.

We considered two attributes to characterize the clild health state with obesity problems, the Body Mass Index (BMI) and the Sleep Hours (SH), respectively represented by the symbols x_1, monotonic ascending, and x_2, descending. Fig. 1 (a) shows the rulers to test the agents in two situations. It has a superior (sup) and an inferior part (inf).

Ruler $\mathbf{x_1}$	**Min_1**	**Max_1**	**Inf_1**	**Sup_1**	**$Ideal_1$**	**$valx_1^1$**
	19	**40**	22	25	23	**40**
Ruler $\mathbf{x_2}$	**Min_2**	**Max_2**	**Inf_2**	**Sup_2**	**$Ideal_2$**	**$valx_2^1$**
	5	15	9	11	10	**5**
Ruler $\mathbf{x_1}$	**Min_1'**	**Max_1'**	**Inf_1'**	**Sup_1'**	**$Ideal_1$**	**$val\_x_1^1$**
	19	40	25	28	26	**40**
Ruler $\mathbf{x_2}$	**Min_2'**	**Max_2'**	**Inf_2'**	**Sup_2'**	**$Ideal_2$**	**$val\_x_2^1$**
	5	15	6	8	7	**5**

(a)

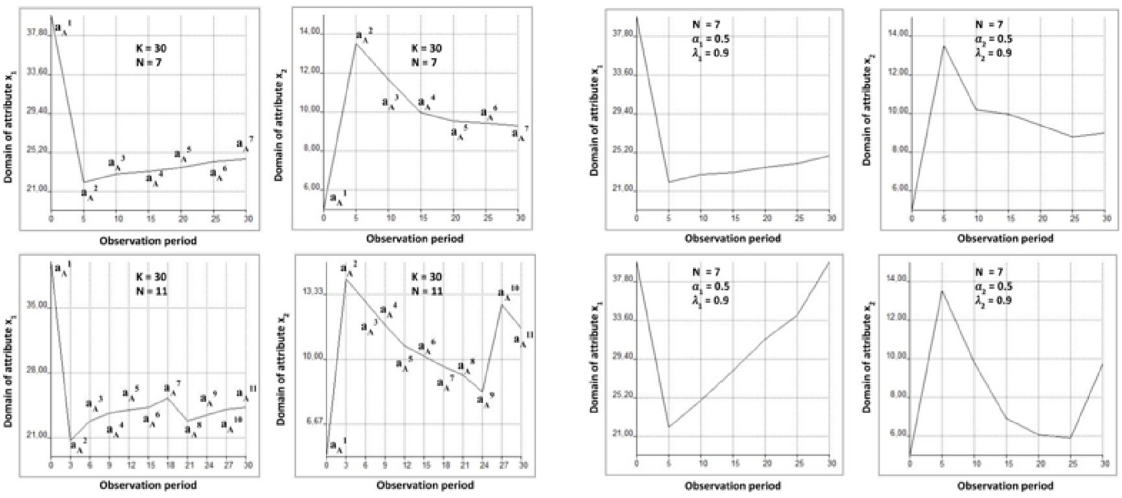
Classification (C1)		Recommendation (C2)		Difference (C3)	
Correct	Incorrect	Correct	Incorrect	Reduction	Increase
1 pt	-1 pt	1 pt	-1 pt	1 pt	-1 pt

(b)

Figure 1. Experimental Settings

Fig. 1 (b) shows the adopted performance measure, considering three criteria during the observation period, in each interaction: (C1) satisfactory operation of the classification mechanism in the `NextA` function; (C2) satisfactory operation of the decision-making subsystem, i.e., of the recommendation mechanism in the `ActionA` function; and (C3) rationality of the agent as a whole, i.e., the effect of the recommended actions in terms of reducing the detected differences in the child's health state in an interaction k.

Fig. 1 (a) defines the fictional ruler employed by the agents in two experiments (E1 and E2), that is, `Health_Advisor` and `Child` have the same ruler. In E1 we set the same value for the parameters of the two agents. Fig. 2 shows the actions effect, during a total time of $K = 30$, and two numbers of interactions: $N = 7$ and $N = 11$. Related to the performance measure, criteria by C1 e C2, we observed an oscillation in the values of x_2 when $N = 11$, the performance was satisfactory, as it pointed maximally in almost all episodes when $N = 7$. In E2 we change the values of parameters. The superior part of Fig. 2 (a) shows the actions effect, with $K = 30$ and $N = 7$. The change accelerated the convergence of x_2 to the adequate values.



(a) (b)

Figure 2. Experimental Results

The inferior part of Fig. 1 (a) defines a different fictional ruler for `Child` in the third experiment (E3). The inferior part of Fig. 2 (b) shows the effect of actions. The `Health_Advisor` agent performed worse than the case where he had the same ruler as the `Child` agent in the superior part of Fig.1 (a). Experiments E1 and E2 are the case that agent performs best than in E3, because he knows exactly the child' ruler.

4. Conclusion

This paper describes the first phase of an agent-based approach to recommend eating and physical activities to children. Although in the beginning, the validation process showed that the approach is promising, but it needs to be continued to better validate the proposed agent called `Health_Advisor`. In the next phase of the design process, we intend to elaborate new experiments trying to perceive the influence of some parameters associated to the agent called Child, and the real consequences for the performance of `Health_Advisor` in the case it has a different ruler from the `Child`.

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