M-SVR Model for a Serious Game Evaluation Tool

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Abstract*— Today, due to their interactive, participatory and entertaining nature, the Serious Games set themselves apart from other learning methods used in teaching. Much progress has been made in the design techniques and methods of Serious Games, but little in their evaluation. In order to fill this gap, we had proposed in our previous work an evaluation tool capable of helping practitioners to evaluate Serious Games in different training contexts. This evaluation tool for Serious Games is designed around four dimensions, namely the pedagogical, technological, ludic and behavioral dimensions, which are measured by clearly defined criteria. During this process, it was highlighted that the human factor (evaluator) influences considerably the result of the weightings through the choice to weight the evaluation dimensions of the Serious Games. In order to reduce this influence during the evaluation process and to keep the correlation between the variables of our evaluation system, we present in this paper, an improvement of our evaluation tool by equipping it with an intelligent supervised self-learning algorithm allowing self-regulation of the weights according to the context of use of the Serious Game to be evaluated. Thanks to the experimental verification of the optimization results, the root mean square error and the coefficient of determination are 0.016 and 98.59 percent respectively, indicating that the model has high precision which guaranteed better predictive performance. A comparison was made between this intelligent model and the models presented in our previous work; the results obtained indicated the same order of the four dimensions, and this by reducing the influence of the human factor during the Multi-Output Support Vector Regression weighting process.

Keywords—Serious game; evaluation tool; multi-output support vector regression

I. Introduction

Serious Games are increasingly present in any innovative educational strategy aimed at effective and motivating learning [1]. However, before endorsing a serious game in any training, it is essential to evaluate it in addition to evaluating its impact [2], [3].

In [4], we have presented a serious game evaluation tool based on four dimensions, {Pedagogical (P), Technological (T), Ludic (L) and Behavioural (B)}, that a serious game must satisfy in order to perform the task for which it was designed. In addition, given that the importance of one dimension compared to another depends on the context in which the serious game is used, the fuzzy multi-criteria decision making methods fuzzy AHP, fuzzy TOPSIS, and fuzzy ELECTRE have been used [5], to validate the choice of the weighting of these dimensions.

In conclusion of this work, it is demonstrated that the human factor has a significant influence on the result of weightings when choosing weights for the serious game evaluation dimensions. This is done by favouring, during the weighting process, a higher value of one dimension over another.

Indeed, depending on the context of use of the serious game to be evaluated, the evaluator favours one or more dimensions deemed to be more important. For example, in a Context where the order of the dimensions is as follows P>T>L>B, the evaluator can assign, to the dimensions, all possible percentages satisfying the order of the chosen context of use and this while ensuring that their sum equals 1.

And so, to reduce this human influence in the serious game evaluation process through the choice of weightings of the evaluation dimensions, we present in this paper an improvement of our evaluation system, by endowing it with an automatic algorithm intelligent supervised learning, allowing self-regulation of the weightings according to the context of use of the serious game to be evaluated.

Thus, the Multi-Output Support Vector Regression (M-SVR) will analyze the context data of use of the serious game to allow the evaluation system to build its reasoning system without having to impose a program beforehand. In this learning phase, the algorithm is based on several examples of data to find the existing patterns in the data allowing it to build a model that will be evaluated subsequently in order to estimate its general predictive accuracy for future data.

In this paper, we advocate the use of an intelligent supervised machine learning algorithm to self-regulate weights according to the serious game context of use, to minimize this human influence in the serious game evaluation process.

This paper is divided into four sections. In Section 1, the problem, the formalization and the postulated hypotheses are presented. The description of the proposed model is illustrated in Section 2. Section 3 presents the modeling process steps carried out, together with the obtained results. In Section 4, a general conclusion is provided.

II. Problem - Formulation and Hypotheses

As mentioned above, this work is based on the findings made in our previous work that can be summarized in the following points.

A. *Influence of the Human Factor (the Evaluator) in the Choice of Weightings of the Serious Game Evaluation Dimensions*

As shown in Fig. 1, the evaluator participates in the serious game evaluation process by choosing the ordering of the evaluation dimensions according to the context of use of the serious game to be evaluated.

For example, if the serious game is used in a purely formative context, the evaluator will consider the pedagogical dimension as dominant over the other dimensions.

However, if the evaluator errs in his judgment of the adequacy between these choices of ordering of evaluation dimensions and the context of use of the serious game, then the entire evaluation system will be biased.

B. *Existence of Correlation between the Variables of our Evaluation System*

By analysing our evaluation system, we note the existence of dependency relations between its variables. Thus, we note that there is a relationship between the weighting variables expressed by their sum, which must be equal to 1. Likewise, there is a direct relationship between the evaluation dimensions' variables (P, T, L, B) and the serious game context of use. Fig. 2 presents four main cases of serious game context of use classified according to their main dominant factor: Pedagogy (Fig. 2(a)), Technology (Fig. 2(b)), Ludic (Fig. 2(c)), and Behaviour (Fig. 2(d)).

In each major type of the serious game context of use and according to the ordering of the other dominated factors, we obtain a finite number of serious game contexts of use (branches of the tree).

We also note that in each tree branch, we have an infinite number of possible serious game contexts of use. For example, take the serious game context of use (P > T> L> B) (Fig. 2(a)) where each branch (P > T) or (T > L) or (L > B) will be interpreted, as a weighting value (y_1(P) > y_2(T)), (y_2(T) > y_3(L)) and (y_3(L) > y_4(B)) respectively. With (y_1, y_2, y_3, y_4) varying between 0 and 1 that generates an infinite number of possibilities.

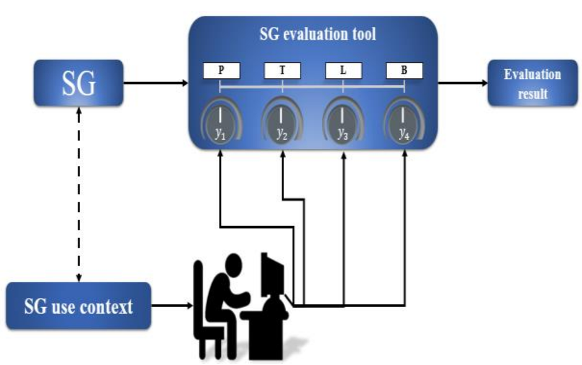

Fig. 1. Serious Game Evaluation Process.

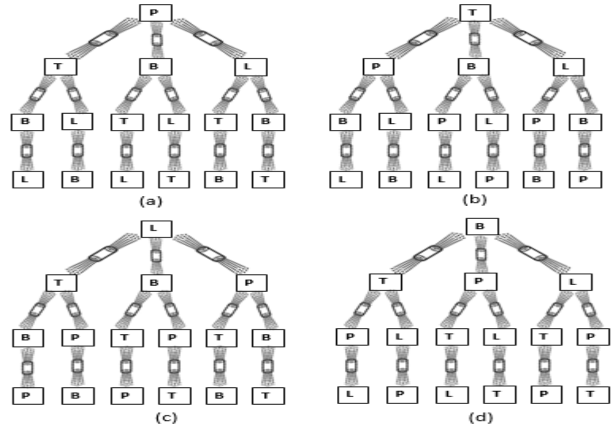

Fig. 2. Possible Serious Game use Contexts.

The Serious Game context of use is represented by the vector $X = \{x_1, x_2, x_3, x_4, x_5, x_6\}$. It is assumed that the serious game type to be evaluated corresponds to its context of use. The number of elements of this vector is deduced from the pair-to-pair comparison of the four dimensions of the evaluations with $(x_i) \in]0, 9]$ Table I.

TABLE I. Example of Representation of Context of Serious Game use

Dimensions Pairwise comparison	Vector X
(P, T)	x_1 =5
(P, B)	x_2 =7
(P, L)	x_3 =8
(T, B)	x_4 =3
(T, L)	x_5 =4
(L, B)	x_6 =0.5

Likewise, the weighting vector represented by $Y = \{y_1, y_2, y_3, y_4\}$, respectively determines the weighting of each dimension {P, T, L, B}. With $(y_i) \in]0, 1]$ is considered as a continuous dependent variable.

III. State of the Art

In order to minimize the evaluator influence during the choice of dimension weights in serious game evaluation process and keep the correlation between the variables of our evaluation system, we believe that it is wise to use the supervised machine learning algorithms power to self-regulate the weightings according to the serious game context of use to be evaluated. Among the machine learning algorithms that can meet our need, there are multi-output regression algorithms [6]. These algorithms, using a single model, aim to simultaneously predict several continuous variables when a common collection of input variables is given [7]. This takes into account not only the underlying relationships between the input variables and the corresponding targets, but also the relationships between the correlated targets [8]. This guarantees better predictive performance [16].

This algorithm type has received a lot of attention from the machine learning science community. It has already proven itself in a wide variety of real life applications [9] such as health [10], [13], wind speed [11], heating load in buildings. Energy efficiency [12], natural language processing [14] and bioinformatics [15].

Among the multi-output regression algorithms, we opted for the multi-output support vector regression (M-SVR) algorithm proposed by Pérez-Cruz et al. [19]. This choice was dictated by:

- The infinite number of input vectors of our system, which represent the evaluation of serious game context of use and the number of output vectors, which represent the weighting, values of the dimensions of evaluation.
- Its ability to predict with high certainty multiple correlated outputs as shown in [24], [25].

IV. Proposed Model

The model proposed in this paper is an intelligent evaluator of serious game that can be adapted to any type of serious game depending on its context of use. As shown in Fig. 3, our evaluator system will be endowed with an intelligent supervised self-learning algorithm.

Therefore, the M-SVR will make it possible to simultaneously self-regulate the weightings $\{y_1, y_2, y_3, y_4\}$ of each dimension according to the serious game context of use to be evaluated $X = \{x_1, x_2, x_3, x_4, x_5, x_6\}$, by capturing all existing dependencies and internal relationships, in order to give better performance (Fig. 4).

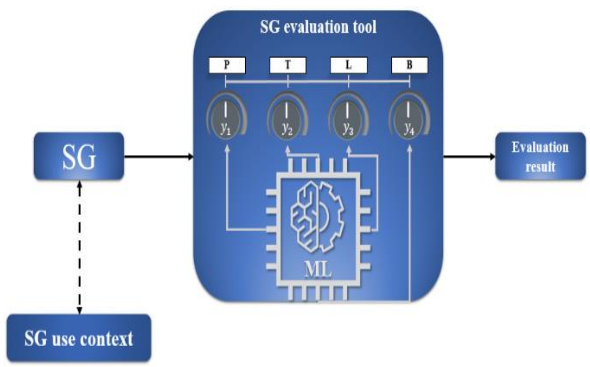

Fig. 3. Intelligent System of Weightings of the Serious Game Evaluation Dimensions.

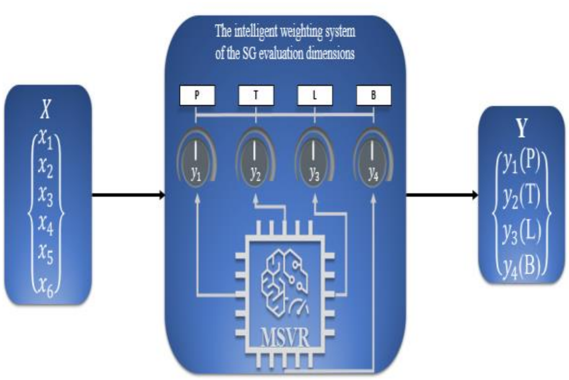

Fig. 4. M-SVR as Intelligent System Implemented in an Evaluator Tool.

A. Algorithm Description

As presented in [19], the M-SVR goal is to find the regressor w^j and b^j (j = 1,…., m) for each output which minimizes the following function (1):

$$\min_{W,b} L_p = \frac{1}{2}\sum_{j=1}^{m}\left\|w^j\right\|^2 + C\sum_{i=1}^{N} L(u_i) \tag{1}$$

Where:

$$u_i = \|e_i\| = \sqrt{e_i^T e_i}\,, e_i^T = y_i^T - \varphi(x_i)^T W - b^T$$

$W = [w^1, \dots, w^m]$: Vector of coefficients of the multiple outputs,

$b = [b^1, \dots, b^m]^T$: The constant vector representing the bias of each output,

C : The regularization parameter that balances the complexity of the model and the approximation precision,

$\varphi(.)$: Denotes a nonlinear mapping of n-dimensional input space to m-dimensional feature space, $\mathbb{R}^n \to \mathbb{R}^m$.

$L(u)$ is an ε-insensitive quadratic cost function, defined by the following equation:

$$L(u) = \begin{cases} 0, u < \varepsilon \\ u^2 - 2u\varepsilon + \varepsilon^2, u \geq \varepsilon \end{cases} \tag{2}$$

When ε = 0, in equation (2), this problem boils down to an independent regularized kernel least squares regression for each component.

For ε ≠ 0, it will take into account all the outputs to build the regressors for each individual, to then produce a single support vector for all the dimensions, in order to obtain more robust predictions. To solve equation (1), an iterative method called iteratively re-weighted least squares (IRWLS) [21] was used in [20], [22].

V. Steps Carried Out in the Modelling Process

The machine learning goal, implemented in our evaluation system, is to allow the multi-output regression algorithm (M-SVR) to learn a correspondence between the input vector (X) $X^{(i)} = \left(x_1^{(i)}, \dots., x_n^{(i)}\right)$ and the output vector (Y) $Y^{(i)} = \left(y_1^{(i)}, \dots, y_m^{(i)}\right)$ from the training data set (D) $D = \left\{\left(X^{(i)}, Y^{(i)}\right)\right\}_{i=1}^{N} \subset \mathbb{R}^n \times \mathbb{R}^m$ for N samples. Therefore, find a function h, which relates the input vector X to the output vector Y, $h(X) = Y$.

And so, for a given new input vector $\hat{X}$, the model will be able to predict an output vector $\hat{Y}$. $\hat{Y}$ = h ($\hat{X}$) which best approximates the real output vector Y.

Fig. 5 shows the process of machine learning algorithm like M-SVR, which consists of three main steps:

In our experiment, we used the implementation of the M-SVR algorithm with the programming language Python, using the machine-learning library Scikit-Learn [23]. The initial setup was done with the kernel = 'rbf', γ = 0.001, ε = 0.001 and C = 40.

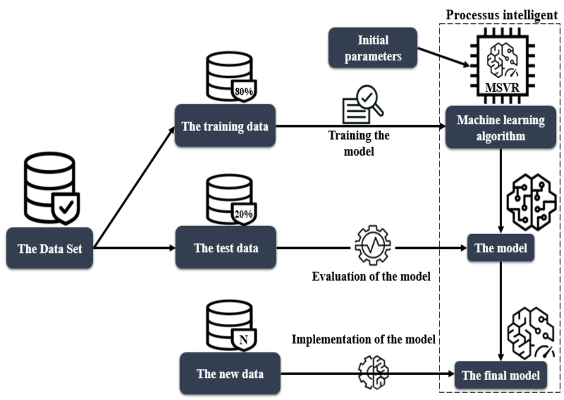

Fig. 5. Steps carried out in the Modelling Process.

A. Model Training

In the training phase of the model, we used the training data from the set (D). $D = \{ (X^{(i)}, Y^{(i)}) \}_{i=1}^{N}$. With N = 2500 knowing that the complexity of the adjustment time is more than quadratic, which makes it difficult to adapt the M-SVR to data sets of more than 10000 samples. Table II shows an example of the pair of training vectors (X, Y) used in this step.

The input vector (X) $X^{(i)} = (x_1^{(i)}, \ldots, x_n^{(i)})$ and the output vector (Y) $Y^{(i)} = (y_1^{(i)}, \ldots, y_m^{(i)})$ with n = 6 and m = 4.

We followed the recommendations mentioned in the scientific literature of Machines Learning, taking 80% of the learning data as model training data and 20% of the training data as model evaluation data.

TABLE II. TRAINING DATA

Input vectors: serious game contexts of use's						Output vectors: evaluation dimensions weightings'			
x_1	x_2	x_3	x_4	x_5	x_6	y_1	y_2	y_3	y_4
0.5	3	0.2	0.2	0.5	0.5	0.135	0.133	0.154	0.578
7	1	7	3	5	3	0.508	0.234	0.196	0.062
5	1	3	7	9	5	0.387	0.371	0.182	0.06
3	5	5	0.142	7	7	0.514	0.134	0.307	0.045
7	3	0.125	5	3	5	0.307	0.293	0.189	0.212
7	3	3	5	7	0.333	0.527	0.279	0.076	0.118
0.333	5	0.125	3	0.142	1	0.138	0.214	0.104	0.544
0.2	1	0.2	1	0.2	3	0.100	0.223	0.290	0.386
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
0.5	3	0.2	5	0.2	0.5	0.128	0.247	0.076	0.549
3	5	7	5	5	7	0.540	0.293	0.124	0.043

B. Model Evaluation

After the training phase, the evaluation data is used to evaluate the performance of the model based on the statistical measure R^2.

This statistical measure represents the quality of the regression model adjustment. The closer the value of R^2 is to 1, the more accurate the regression model [18].

$$R^2 = \frac{SS_{reg}}{SS_{tot}} = 1 - \frac{SS_{err}}{SS_{tot}} \quad (3)$$

Where SS_{reg} the sum of squares is explained by the regression, SS_{tot} refers to the total sum of squares and SS_{err} is the sum of the squared error.

In addition, the root mean square error (RMSE) [17] is calculated to have the standard deviation of the errors that occur when a prediction is made on a data set. The closer the value is to 0, the less error the model produces.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} \| y(i) - \ddot{y}(i) \|^2}{N}} \quad (4)$$

Where N is the number of data items, $y(i)$ is the ith measure, and $\ddot{y}(i)$ is its corresponding prediction.

The results in Table III give a value of RMSE = 0.016 and R^2 = 98.59%. From these values, we can deduce that the accuracy of the prediction model is acceptable and, therefore, we can proceed to the exploitation of the model.

C. Model Exploitation

Once the model is trained, tested and validated, we were able to exploit it by introducing new input values $\hat{X}_i$ characterizing contexts of use of possible serious games for the prediction of the weighting values of the weighting dimensions evaluation of serious game $\hat{Y}_i$. Table IV shows an example of the operating values of the model.

TABLE III. MODEL TEST

Test input vectors						Real output vectors				Model output vectors			
x_1	x_2	x_3	x_4	x_5	x_6	y_1	y_2	y_3	y_4	$\ddot{y}_1$	$\ddot{y}_2$	$\ddot{y}_3$	$\ddot{y}_4$
7	3	0.125	5	0.125	3	0.271	0.117	0.147	0.465	0.270	0.126	0.140	0.462
7	1	7	3	5	1	0.524	0.241	0.153	0.082	0.519	0.237	0.146	0.094
3	3	7	7	7	0.333	0.492	0.357	0.065	0.087	0.444	0.409	0.070	0.077
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
1	1	3	7	9	9	0.242	0.515	0.195	0.049	0.249	0.497	0.190	0.060
9	5	0.125	3	0.142	3	0.317	0.098	0.144	0.441	0.304	0.102	0.138	0.454

TABLE IV. PREDICTION OF DIMENSION WEIGHTS

New Input Vectors						**Model output vectors**			
$\hat{x}_1$	$\hat{x}_2$	$\hat{x}_3$	$\hat{x}_4$	$\hat{x}_5$	$\hat{x}_6$	$\hat{y}_1$	$\hat{y}_2$	$\hat{y}_3$	$\hat{y}_4$
3.3	3	5	3	5	3	0.500	0.283	0.163	0.056
5	3	5	3	2	3	0.543	0.181	0.160	0.119
1	5	3	5	7	3	0.350	0.483	0.107	0.060
5	3	1	3	2	3	0.351	0.180	0.179	0.291
1	3	3	7	7	3	0.295	0.527	0.116	0.060
2	1	2	7	7	6	0.271	0.471	0.192	0.063
5	3	1	3	2	7	0.345	0.198	0.242	0.217

We also tested our evaluator model with the M-SVR model using the same evaluation context proposed in [4], where the context of use of the serious game is purely educational, with an academic and scientific target audience.

The vector X = {3,5,7,3,5,3} represents the context of use and the corresponding output vector generated by the M-SVR model is Y = {0.557,0.270,0.123,0.052}. The serious game to be evaluated is "Leuco'war", Fig. 6 illustrates the results obtained which confirm those obtained in [4].

According to the results obtained, we note that the use of the M-SVR algorithm at the centre of the weighting process of the chosen dimensions has provided our serious game evaluation tool the ability to self-regulate with an acceptable precision the weights of the dimensions in different Serious Game evaluation contexts. This allowed us to respond to the observations noted during the experimental studies conducted in [4], [5]. Indeed, M-SVR, using a unique predictive model of several continuous variables, guaranteed a better predictive performance confirmed by the values of RMSE and R^2 respectively equal to 0.016 and 98.59 per cent. This by taking into consideration the underlying relationships between the context variables of use of the Serious Game and the weights of the corresponding dimensions, and their correlated relationships. Likewise, the comparison of the results obtained by this evaluation model confirms, with a notable reduction in the influence of the human factor in the process of weighting of dimensions, the same order of its last obtained in [4], [5].

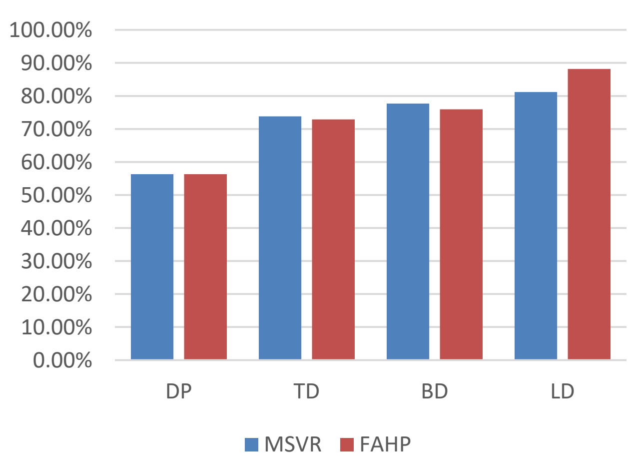

Fig. 6. Serious Game "Leuco'war" Evaluation Results.

Finally, we note that the most important added value of the use of the M-SVR multi-output supervised machine learning algorithm is its ability to adapt the weightings of the serious game evaluation dimensions to the very large number of possible contexts of use.

VI. CONCLUSION

By introducing a smart process such as M-SVR into our serious game evaluator system, we were able to reduce the subjective evaluation introduced by the human factor by having automatic weighting values according to the context of use of the chosen serious game. In addition, the values of the test parameters RMSE and R^2 equal to 0.016 and 98.59% respectively testify to an acceptable performance of the algorithm used. However, we noticed an instability of the algorithm when we used a very large dataset volume. Thus, we plan to compare the results obtained with M-SVR with another other algorithms of the same type that is more stable with respect to the volume of the data set of more than 10000 samples, because the complexity of the adjustment time is more than quadratic. Likewise, we plan to place an intelligent process in our system linking the serious game context of use and the corresponding serious game.

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