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TOWARDS EFFICIENT ELEMENTARY SCHOOL EDUCATION: A SERBIAN PERSPECTIVE

In this paper, a vector correlation coefficient (VCC) has been utilized as an evaluation measure. Using this approach, those schools have been identified in which students both performed greatly in school and at their entrance exams. Furthermore, those schools that suffer from scholastic inconsistency have been shown to have the following: high average marks but poor exam performance and vice versa. In accordance with this, framework for evaluating elementary school performance is proposed.

Keywords: *elementary school education; school effectiveness; ranking; statistical methods.*

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ДО ЕФЕКТИВНОЇ ПОЧАТКОВОЇ ОСВІТИ: СЕРБСЬКА ПЕРСПЕКТИВА

У статті використано векторний коефіцієнт кореляції як міру оцінювання ефективності шкіл. Використовуючи цей підхід, було визначено, в яких школах учні показали високий результат як у навчанні, так і під час вступних іспитів. Школи, в яких страждає система викладання, продемонстрували наявність високих оцінок, але низькі результати на іспитах, і навпаки. Відповідно до цього запропоновано базову концепцію системи оцінювання успішності в початковій школі.

Ключові слова: *початкова освіта; ефективність роботи школи; ранжування; статистичні методи.*

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К ЭФФЕКТИВНОМУ НАЧАЛЬНОМУ ОБРАЗОВАНИЮ: СЕРБСКАЯ ПЕРСПЕКТИВА

В статье использован векторный коэффициент корреляции в качестве меры оценки эффективности школ. Используя этот подход, было определено, в каких школах ученики показали высокий результат, как в учебе, так и на вступительных экзаменах. Школы, в которых страдает система преподавания, продемонстрировали наличие высоких оценок, но низкие результаты на экзаменах, и наоборот. В соответствии с этим предложена базовая концепция системы оценивания успеваемости в начальной школе.

Ключевые слова: *начальное образование; эффективность работы школы; ранжирование; статистические методы.*

1. Introduction. The evaluation of higher education institutions (HEI) has drawn a lot of attention lately. Prospective students and general public use evaluation reports and rankings as an indicator of a university's reputation and performance (Billaut , Bouyssou & Vincke, 2010; Dehon, McCathie & Verardi, 2010; Docampo, 2011; Jeremic et al., 2011; Jovanovic et al., 2012). However, it is often neglected that university education is only the third chapter of continuous education that starts with elementary school. Since these schools are very often cited as being the most crucial component of education (Bekleyen, 2010), it is of great concern whether elementary schools are effective (Petty

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& Green, 2007). In contemporary literature on the subject, there have been several attempts to evaluate school effectiveness (Kyriakides & Tsangaridou, 2008; Kyriakides & Creemers, 2008a; Kyriakides & Creemers, 2008b; D'Haenens, Van Damme & Onghenab, 2010; Botha, 2010). In this article, the following novel approach shall be presented: students' enrollment into high school clearly evaluates their degree of knowledge adopted during their eight-year long elementary education. The level of knowledge represented at entrance examinations can also be used to rank elementary schools, based on the results of their students. By using a vector correlation coefficient, the level of how well students use their knowledge acquired during their elementary school education at their entrance exams can be shown. Thereafter, a quantitative assessment of how much one school is better or worse than another can be made.

In section 2, vector coefficient of the correlation methodology is elaborated upon, Section 3 presents and discusses the results of this research project and, finally, Section 4 summarizes the key contributions of the manuscript to proper scholastic evaluation.

2. Methodology.

Using a two-dimensional random variable (X, Y), the total variability is given by the dispersion matrix:

$$W = \begin{bmatrix} \sigma_1^2 & \sigma_{12} \\ \sigma_{21} & \sigma_2^2 \end{bmatrix}$$

It is known that the so-called generalized variance for (X, Y) is defined through the dispersion matrix:

$$g - Var(X,Y) = \det W - |W|$$

The determinant of the dispersion matrix has the maximum value when X and Y are independent variables. The maximum value is then:

$$\max|W| = \sigma_1^2\sigma_2^2, \text{ (Vukovic, 1976)}$$

This will have the minimum value of (zero) if and only if X and Y are linearly dependent values:

$$0 \le W \le \max|W| = \sigma_1^2\sigma_2^2$$

The determinant can be calculated by multiplying the maximum value with one of the factors (Lakhera et al., 2011; Prasad et al., 2011). Marking that factor as ($1—\rho^2$), it emerges as:

$$|W| = \max|W|(1-\rho^2) = \sigma_1^2\sigma_2^2(1-\rho^2),$$

where ρ is the correlation coefficient (Al-Lagilli et al., 2011; Jeremic et al., 2011d,e). Supposing that Z is a $(n+m)$-dimensional random variable so that

$$Z = (X,Y); Y = (Y_1,\ldots,Y_m); X = (X_1,\ldots,X_n).$$

The expected value of variable Z is marked as:

$$m_z = (m_y, m_x); m_y = (m_{y1},\ldots,m_{ym}); m_x = (m_{x1},\ldots,m_{xm}),$$

and the expected disperse matrix is

$$W = \begin{bmatrix} W_{yy} & W_{yx} \\ W_{xy} & W_{xx} \end{bmatrix},$$

W_{yy} is a disperse matrix of vector Y components;

W_{xx} is a disperse matrix of vector X components;

W_{yx} is a covariance matrix of vector Y and vector X components.

Result 1. The generalized variance of the random variable Z is given (Ivanovic, 1977; Jeremic et al., 2011a,b,c) by the expression

$$|W| = |W_{yy} - W_{yx}W_{xx}^{-1}W_{xy}||W_{xx}|$$

Result 2. The generalized variance of the random variable Z satisfies the inequality

$$0 \le |W| \le |W_{yy}||W_{xx}|$$

Result 3. The generalized variance of the random variable Z has the maximum value when the vectors Y and X are independent (Dobrota et al., 2012; Jeremic et al., 2012).

Definition: The value marked as R_v is given by the expression

$$|W| = (1 - R_v^2)\max|W| = (1 - R_v^2)\max|W_{yy}||W_{xx}|$$

and is called the vector correlation coefficient between the *m*-dimensional variable Y and the *n*-dimensional variable X (Vukovic, 1976).

Result 4.

$$R_v^2 = 1 - \frac{|W|}{|W_{yy}||W_{xx}|} = 1 - \frac{|W_{yy} - W_{yx}W_{xx}^{-1}W_{xy}|}{|W_{yy}|}$$

Result 5. For m=1, R_v is the multiple correlation coefficient, and for m=1, n=1, R_v is merely a plain correlation coefficient (Knezevic et al., 2012; Radojicic et al., 2012).

Result 6.

a) $0 \le R_v^2 \le 1$

b) $R_v^2 = 1 \Leftrightarrow$ {*Y* and *X* are linearly dependent}

c) R^2_v=0 when components Y and X are mutually non-correlated, i.e. when $W_{yx}=0$

d) For mutually independent vectors Y and X, R^2_v=0

Result 7.

$$R_v^2 = 1 - \frac{|R|}{|R_y||R_x|}$$

R — correlation matrix Z, R_y — correlation matrix Y, R_x — correlation matrix X.

3. Results and analysis. At the end of the 2004-2005 school year, 18 elementary schools in Belgrade (the capital of Serbia) were examined. Overall, 1,352 students were analyzed in this study. For each student, the following information was gathered: the grade point averages (minimum 1, maximum 5) of the school's students in the 6th, 7th and 8th grades were used as input variables, while their scores on their math and Serbian (native) language tests (minimum 0, maximum 20 — for both tests) were used as output variables. In accordance to this grading system, only the total maximum of 60 points can be achieved in one's marks from elementary school (the sum of GPAs for the 6th, 7th, 8th grades, multiplied by 4). However, the maximum of 40 points can be obtained from the tests (20 points multiplied by two (math and Serbian language test)). This data was used (as is shown in table T1) to calculate Rv2 (vector correlation coefficient). To achieve this aim, a special SPSS plug-in was developed and implemented into SPSS 17 software.

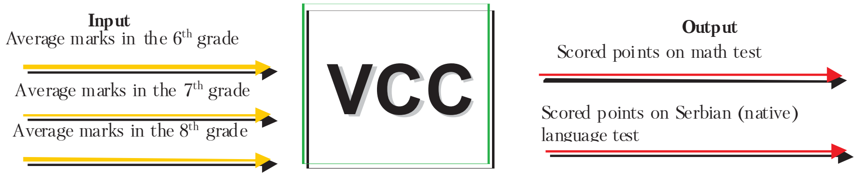

Table T1. **Table of the average results delineated by school**

School	Sample Size	R_v^2	Avg. Grade 6	Avg Grade 7	Avg. Grade 8	Avg. Math	Avg. Na-tive La-nguage	Fi-nal Scores	Entra-nce Exam	Sum
School# 1	42	0.842	4.537	4.426	4.349	16.464	17.298	53.247	33.762	87.009
School# 2	58	0.512	4.476	4.430	4.488	16.638	17.267	53.577	33.905	87.482
School# 3	31	0.670	4.295	4.161	4.238	16.952	16.129	50.774	33.081	83.855
School# 4	79	0.475	3.851	3.694	3.754	16.658	16.424	45.193	33.082	78.276
School# 5	51	0.530	4.122	3.935	4.004	15.980	15.833	48.242	31.814	80.056
School# 6	76	0.514	3.936	3.849	3.862	15.572	16.296	46.587	31.868	78.455
School# 7	65	0.717	3.979	3.959	3.976	14.485	15.392	47.655	29.877	77.532
School# 8	68	0.639	4.151	4.021	4.084	13.353	15.699	49.024	29.051	78.075
School# 9	78	0.520	4.202	4.261	4.331	13.006	14.756	51.179	27.763	78.942
School# 10	92	0.637	3.757	3.608	3.755	11.902	12.957	44.477	24.859	69.335
School# 11	101	0.558	4.112	3.921	4.015	13.119	14.347	48.192	27.446	75.638
School# 12	146	0.562	4.086	4.023	4.073	11.298	13.688	48.728	24.986	73.714
School# 13	129	0.655	4.156	4.082	4.100	12.109	14.570	49.350	26.678	76.028
School# 14	80	0.739	4.071	3.937	4.103	11.119	13.950	48.440	25.069	73.509
School# 15	77	0.759	4.153	4.013	4.116	13.117	14.604	49.127	27.721	76.848
School# 16	71	0.729	3.992	3.914	3.881	10.345	12.486	47.147	22.831	69.978
School# 17	68	0.733	4.311	4.119	4.236	15.647	17.324	50.663	32.971	83.633
School# 18	40	0.554	4.194	4.101	4.277	19.225	18.363	50.288	37.588	87.876

As can be seen from Table 1, a vector correlation coefficient was calculated (R^2_v) for each of 18 schools. A high value of R^2_v implies a high correlation between input and output variables. In the case presented here, students coming for schools with high average marks are expected to do well in their math test and test of their native language. If so, they have a correspondingly good R^2_v value (e.g., School#1). The same conclusion can be applied for the schools, in which students are not as successful (lower average marks) and similarly perform in the same tests (e.g., School#16).

In particular, the analysis here has singled out the schools with lower R^2_v values. This essentially means that students with lower average marks in elementary school, outperformed on their tests (e.g., School#4). Moreover, those schools that have excellent average marks but poor test performance have also low R^2_v values (e.g., School#12). These schools are of great research interest, as high average marks which are not confirmed by adequate test performance can easily indicate that professors in these schools are not strict enough in their grading. On the other hand, lower average marks in school and an excellent number of points in tests indicate that students are awarded with lower marks than they actually deserve. Nonetheless, there are some inconsistencies noted by the method used. For instance, when School#1 and School#2 are compared, it can be noted that they have very similar average marks for all the grades (6th, 7th and 8th) and have a similar number of points achieved in both their native (Serbian) language (NL) and math tests. However, School#1 has a very high R^2_v value (0.842); while, School#2 has a poor R^2_v value (0.512). In order to evaluate the underlying dynamics of this inconsistency, the following chart is presented:

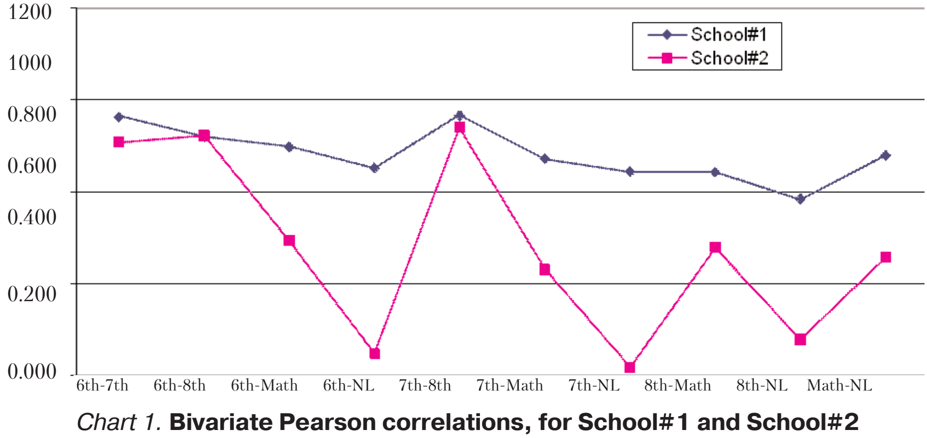

Chart 1. **Bivariate Pearson correlations, for School#1 and School#2**

As can be seen, School#1 has a high consistent correlation between all the variables. On the other hand, School#2 has huge fluctuations and far smaller values of correlations. The correlation between the average marks of the 6th and 7th/ 6th and 8th/7th and 8th grades are high and consistent for both schools. However, there is a huge drop in the correlation for School#2 when each year's average mark is compared to the points achieved at the entrance tests. All of this reflects the poor value of R^2_v for School#2.

4. Conclusion. The aim of this paper is to determine the interrelationships between elementary school education and secondary school entrance exams. This particular research issue is very much neglected in contemporary research papers. While a few authors have tried to examine this issue from the perspective of the socio-economic background of the students (Mohammadi, Akkoyunlu & Seker, 2011), no research has been carried out — as far as it is known to the authors of this paper — with the sole purpose of evaluating the correlation between students' average marks in elementary school and the points they scored at their secondary school entrance test. With the methodology presented in this work, the inner perspective of elementary school effectiveness has been able to be effectively shown. The vector correlation coefficient has demonstrated "good schools" as those in which students have excellent GPA as well as showing their corresponding performance in entrance tests (both in their native language and in math). A special contribution of the analysis carried out here is that the schools are presented that suffer from irreconcilable inconsistencies; particularly, schools where students have excellent average marks but perform poorly in entrance tests. These results indicate lower standards in grading students as they have excellent marks. However, an overall lack of knowledge exists in these students, which is reflected in their low scores obtained for their entrance exams. The analysis presented here may be able to provide a proper framework for evaluation of elementary school education; one possibility would be a national program for continual evaluation of schools, which could also be easily applied throughout the entire country. This particular framework should be implemented by the Serbian Ministry of Education and re-evaluated each year in order to determine whether Serbian elementary school education is on the right track.

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