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Chi-Square Function Applied to Learning Objects Intelligent Learning Mechanisms

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Abstract: The massive data set obtained from the analysis of a particular cognitive profile requires an evaluation function versatile enough for application to a Genetic Algorithm (GA) in order to be able to make decisions that involve a high degree of reliability - in the order of 90 to 95%.

The problem to be studied is whether it is possible or not to evolve in cognitive terms, through the choice of learning object [7] more suitable, which we denominate as Knowledge Block (KB) - a Sharable Content Object Reference Model (SCORM) compatible structure – see Fig. 2.

The Pearson's Chi-square test (X^2) is the evaluation function selected, because of its simplicity. By observation of merely two parameters — Observed Value (*Oj*) and Expected Value (*Ej*) — we may infer if the hypothesis in test is true, determining in this way if the method is the appropriate.

Keywords: Learning, Evaluation, Chi-square, Cognitive, Profile, Genetic Algorithm,

1. Introduction

Every day, around the world, an immense amount of energy is consumed by millions of young people and adults, to teach and learn. The processes and methods used have centuries and the shortcomings of the system are obvious.

One of the objectives of e-Learning, and particularly of the learning objects [7], is the implementation of new processes that dramatically increase the results obtained in the teaching and learning to the academic level and not only.

If we adapt the initial paradigm of e-Learning, associating extrapolation techniques of the results using a GA and an evaluation function versatile enough to conduct the follow-up of the cognitive profile and determine the learning curve, so that exists a sustainable cognitive growth, we will have meaningful gains.

In this paper, we propose a solution using the Chi-square as the evaluation function and a GA as an intelligent structure that evaluates data from the evaluation function. The GA will send the best solution found to a Learning Management System (LMS) the best solution found, after selecting a KB according to the best solution available - see Fig. 1.

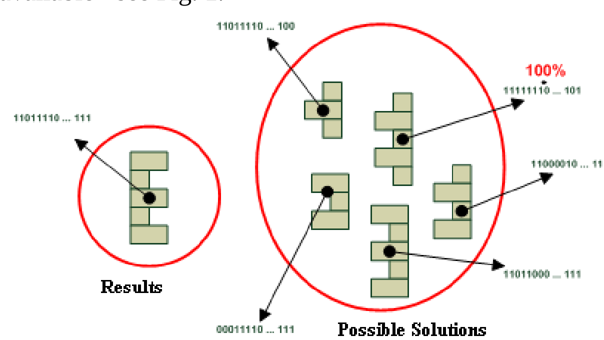

Figure 1. GA (Search for best solution)

2nd Section – Presents the reasons behind the choise of what we will evaluate, why and in what way, an outlook of the main problems we intend to solve, and a brief description of Chi-square function.

3rd Section – Shows a random simulation of Chi-square using Excel and analyzes the obtained data.

4th Section – Presents the conclusions of the work done until now and future perspectives.

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2. CHI-SQUARE AS EVALUATION FUNCTION

A. A brief introduction to what we will evaluate, why and in what way.

The human brain contains four lobes: the occipital, temporal, parietal and frontal lobe. Each one is responsible to different functions — the occipital lobe is the responsible for processing visual information, the temporal lobe processes auditory information and the parietal lobe processes information from somatic sensors and the frontal lobe, which is composed by prefrontal area and motor area, processes the information from the other three lobes and operates the output. There are grads of cortexes in each lobe of the brain, which decide the levels of cognition, e.g. the perceptions pass through lower level of cortexes to higher ones to perform higher cognition tasks — different cognition processes have to make use of different levels of cortexes, where demanding cognition tasks require more cognition steps than easier ones [1].

In knowledge acquisition, memory is the physiological organ or networked neural clusters in the brain for retaining and retrieving information — memorization is one of the cognitive processes of the brain at the meta cognitive layer that establishes (encodes and retains) and reconstructs (retrieves and decodes) information [2]. In this way, we can define cognition as the process by which a sensory stimulus is transformed, reduced, elaborated, stored and recovered for later use.

In agreement with the idea that learners generally learn best when they are given the opportunity to work in their preferred learning style, current research in educational environments has increasingly focused the development of systems that adapt and personalize instructional contents to students' learning method [3]. Two key factors of these innovative means are cognitive style and the use of appropriate e-Learning platforms [3].

So, making knowledge accessible, available and attractive is a fundamental point to determine the developmental capacity through knowledge of the learning curve of a given cognitive profile, potentiating in this way the evolutionary capacity. This can be done with the structure presented in Fig. 2 which in conjunction with the results of the evaluation function will be chosen by the GA according to the available solutions — see Fig. 1.

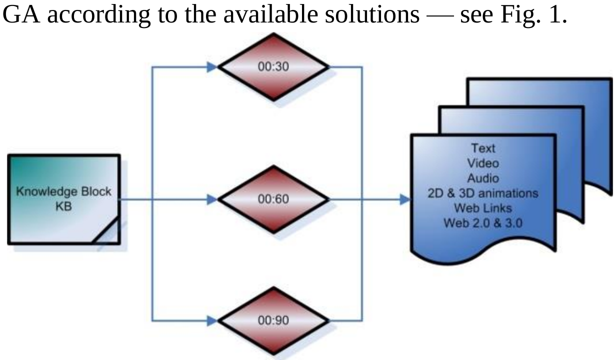


Figure 2. Knowledge Block Structure

The KB is a simple structure that has SCORM compatibility and a binary codification, allowing the GA to select the most suitable option to a specific case.

This structure will manage virtually autonomously a sustainable cognitive evolution. The KB will send the classifying indicators to the AG which through the evaluation function will allow us to decide whether the objectives have been achieved and if there exists any condition to start a higher level.

B. The Outlook.

When moving from traditional learning to educational e-Learning systems students get increasingly involved in their learning process. Technological systems are the new vectors used to disseminate knowledge between (actors, pedagogues, tutors and learners) and provide feedback in the learning process. The use of Information Technology (IT) in education covers a wide range of very different activities; e.g. learning environments, course management, and much more. Because the *one-size-fits-all* paradigm cannot be applied to individual learning, adaptability is a must. Hence, courseware is meant to be tailored according to the learner's needs. Two main families of computerized applications aspire to offer this adaptability: Intelligent Tutoring Systems (ITS) [12] and Adaptive Hypermedia Systems (AHS) [12].

Intelligent Tutoring Systems [12] rely on curriculum sequencing mechanisms to provide the student with a path through the learning material. An adaptability algorithm computes this so-called personalized path, corresponding to the course construction and curriculum sequencing [12]. The process is twofold:

- Find the relevant topics and select the most satisfactory one;
- Dynamically construct page contents based on the tutor decision for what the learner should study next;

IT Systems usually provide an evaluation of the learner's level of mastery of the domain concepts through an answer analysis and error feedback process that eventually allows the system to update the user's model. This process is called intelligent solution analysis [12].

Adaptive Hypermedia (AH) [12] was born as a trial to combine ITS and AH. As in ITS, adaptive education hypermedia focus on the learner, while at the same time it has been greatly influenced by adaptive navigation support in educational hypermedia [12]. In fact, adaptability [12] implies the integration of a student model in the system in the framework of a curriculum, which sequence depends on pedagogical objectives, user's needs and motivation.

Hence, the use of adaptive and/or interactive hypermedia systems was proposed as a promising solution [13]. Adaptivity in e-Learning is a new research trend that personalizes the educational process through the use of Adaptive Educational Hypermedia Systems (AEHS). These systems attempt to create an individualized course according to the user's personal characteristics, such as language, learning style, preferences, educational goals and progress. In this way, instructors expect to solve some of the main problems of web courses and hope to succeed in achieving a better Iearning outcome [13].

However, there is still a problem in the presented families; information comes from different sources embedded in diverse formats into the form of metadata, making it troublesome for the computerized programming to create professional materials [14]. The major identified problems are [14]:

- Difficulty in sharing learning resources;

  Even if all e-Learning systems follow the common standard, users still have to visit individual platforms to gain appropriate course materials and contents. It is comparatively inconvenient;

- High redundancy of learning material;

  Due to difficulty in sharing resources, it is hard for teachers to figure out the redundancy of course materials resulting in the waste of resources, physically and virtually;

  Even worse, the consistency of course content is endangered which might eventually slow down the innovation momentum of course materials;

- Deficiency of the course brief;

  It is hard to abstract a course summary or brief automatically in an efficient way. So, most courseware systems only list the course names or the unit titles. Information is insufficient for learners to judge the quality of the course content before they enroll in certain courses;

TABLE 1.. - KB Coding

Reserved to future use	*Educational Level*	*Cognitive Profile ID*	*KB difficulty level*
00000000	00000	000	0000000000000000

All the identified problems are the result of the following gaps:

- A lack of a standardized structure in the construction of learning objects;
- The learning objects don't have the possibility to evolve or adapt oneself in the future in terms of contents — are closed in themselves;
- There is no versatility enough in classification of learning objects;
- There is no real intelligent structure to follow the entire learning process — quantitative and qualitative analysis, choice of the most appropriate learning object, adequation to the context and final verification;
- Exists always the possibility of a wrong judgment about the quality of a learning object;

The solution that the authors propose to implement solves most of the problems mentioned. Of all the research conducted until the moment, our solution is the only one that integrates the following points:

- Quantitative and qualitative[11] analysis — in a near future — of students' data;

- Standardizing of the learning objects, granting them a base structure with SCORM compatibility — see Fig. 2 — a structured coding — see Table 1 — and an evolutionary capacity;
- Integrated platform with intelligent content management — see Fig. 3 where the entire learning process is controlled;

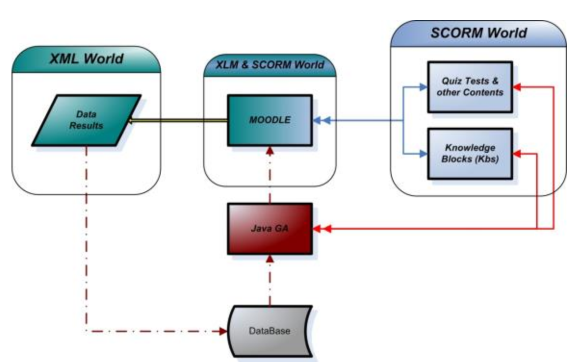


Figure 3. Evolutive Platform Structure

One of the problems that are virtually impossible to be solved is the redundancy of learning materials. This matter is not the scope of this investigation, but one possible solution will be the quality control of the learning objects used by this platform.

C. The Chi-square evaluation function.

The Chi-square is defined as a discrepancy measure between the observed frequencies and the expected ones (1). [5]

The X^2 value is calculated using the following equation:

$$\chi^2 = \sum_{i=1}^{p}\sum_{j=1}^{q} \frac{(n_{ij} - e_{ij})^2}{e_{ij}} \qquad (1)$$

Where p and q is the number of observed values (*Oj)*, e_{ij}, is the expected frequency of symbols, and n_{ij} is the observed frequency. Equation (1) obeys the B-1 degrees of X^2 freedom of distribution and increases when the difference between the expected frequency and the observed frequency is large [8].

The independence test of Chi-square allows you to check the independence between two variables of any type, grouped in a contingency table. This test should not be used if more than 20% of the expected frequencies under the assumption of independence are less than 5 or if any of them is equal to 0 [6].

$$x^2 = \frac{(o_1 - e_1)^2}{ej} + \frac{(o_2 - e_2)^2}{ej} + \ldots + \frac{(o_k - e_k)^2}{ej} = \sum_{j=1}^{k} \frac{(o_j - e_1)^2}{ej}$$

The theory is based mainly on the following two assumptions:

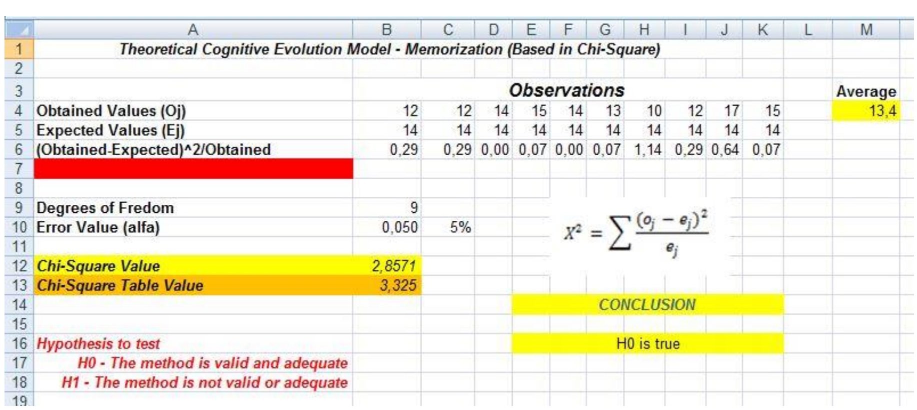
- H_0 — the variables are independent - the method is valid and adequate;
- H_1 — the variables are not independent - the method is not valid or adequate;

Note that the alternative hypothesis does not have any information on the type of association between the variables.

The test works by comparing the observed frequencies of each of the p x q cells, n_{ij}, with the corresponding frequencies expected under the hypothesis of independence, e_{ij}, through the value which is used for the calculation of the coefficient of contingency of Pearson [6] (1) (2).

If this value is small enough then the corresponding "barrier" is established by the significance level of the test, which means that the differences n_{ij} - e_{ij} are small, and we must accept H_0 as the valid hypothesis [6].

3. SIMULATION OF EVALUATION FUNCTION CHI--SQUARE



	A	B	C	D	E	F	G	H	I	J	K	L	M
1	Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)												
2													
3						Observations							Average
4	Obtained Values (Oj)	12	12	14	15	14	13	10	12	17	15		13,4
5	Expected Values (Ej)	14	14	14	14	14	14	14	14	14	14		
6	(Obtained-Expected)^2/Obtained	0,29	0,29	0,00	0,07	0,00	0,07	1,14	0,29	0,64	0,07		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%			$X^2 = \sum \frac{(o_j - e_j)^2}{e_j}$							
11													
12	Chi-Square Value	2,8571											
13	Chi-Square Table Value	3,325											
14					CONCLUSION								
15													
16	Hypothesis to test				H0 is true								
17	H0 - The method is valid and adequate												
18	H1 - The method is not valid or adequate												
19													

Figure 4. Initial Sampling

With 10 initial observations – see Fig. 4, with an expected value (Ej) of 14, the Chi-square result leads us to conclude that the H_0 hypothesis is valid, since the value obtained through the application of the evaluation function is inferior to the value in the distribution table of the Chi-square — 2,8571 against 3,325 respectively.

As we can observe in Fig. 5, when changing the value of cell B5 in *Ej* to the value 15, the Chi-square value is below the reference value in the distribution table of the Chi-square.

When changing the values of cells B5 and C5 in E_J to 15, we can observe that the hypothesis H_0 are no longer valid, because the obtained Chi-square value are slightly superior to the observed in the distribution table of the Chi-square.

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)*												
2													
3						**Observations**							**Average**
4	Obtained Values (Oj)	12	12	14	15	14	13	10	12	17	15		13,4
5	Expected Values (Ej)	15	14	14	14	14	14	14	14	14	14		
6	(Obtained-Expected)^2/Obtained	0,60	0,29	0,00	0,07	0,00	0,07	1,14	0,29	0,64	0,07		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%										
11													
12	*Chi-Square Value*	*3,1714*											
13	*Chi-Square Table Value*	*3,325*											
14						CONCLUSION							
15													
16	*Hypothesis to test*					H0 is true							
17	*H0 - The method is valid and adequate*												
18	*H1 - The method is not valid or adequate*												

$$X^2 = \sum \frac{(o_j - e_j)^2}{e_j}$$

Figure 5. Changing the Expected Value (Ej) of cells B5 to 15

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)*												
2													
3						**Observations**							**Average**
4	Obtained Values (Oj)	12	12	14	15	14	13	10	12	17	15		13,4
5	Expected Values (Ej)	15	15	14	14	14	14	14	14	14	14		
6	(Obtained-Expected)^2/Obtained	0,60	0,60	0,00	0,07	0,00	0,07	1,14	0,29	0,64	0,07		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%										
11													
12	*Chi-Square Value*	*3,4857*											
13	*Chi-Square Table Value*	*3,325*											
14						CONCLUSION							
15													
16	*Hypothesis to test*					H1 is true and H0 is disposable							
17	*H0 - The method is valid and adequate*												
18	*H1 - The method is not valid or adequate*												

$$X^2 = \sum \frac{(o_j - e_j)^2}{e_j}$$

Figure 6. Changing the Expected Value (Ej) of cell B5 and C5 to value 15

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)*												
2													
3						**Observations**							**Average**
4	Obtained Values (Oj)	12	12	14	15	14	13	10	12	17	15		13,4
5	Expected Values (Ej)	15	15	15	15	15	15	15	15	15	15		
6	(Obtained-Expected)^2/Obtained	0,60	0,60	0,07	0,00	0,07	0,27	1,67	0,60	0,27	0,00		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%										
11													
12	*Chi-Square Value*	*4,1333*											
13	*Chi-Square Table Value*	*3,325*											
14						CONCLUSION							
15													
16	*Hypothesis to test*					H1 is true and H0 is disposable							
17	*H0 - The method is valid and adequate*												
18	*H1 - The method is not valid or adequate*												

$$X^2 = \sum \frac{(o_j - e_j)^2}{e_j}$$

Figure 7. Changing the Expected Value (Ej) of all cells to 15

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)*												
2													
3						**Observations**							**Average**
4	Obtained Values (Oj)	13	12	14	15	14	13	11	12	17	15		13,6
5	Expected Values (Ej)	15	15	15	15	15	15	15	15	15	15		
6	(Obtained-Expected)^2/Obtained	0,27	0,60	0,07	0,00	0,07	0,27	1,07	0,60	0,27	0,00		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%			$\chi^2 = \sum \frac{(o_j - e_j)^2}{e_j}$							
11													
12	*Chi-Square Value*	*3,2000*											
13	*Chi-Square Table Value*	*3,325*											
14							CONCLUSION						
15													
16	*Hypothesis to test*						H0 is true						
17	*H0 - The method is valid and adequate*												
18	*H1 - The method is not valid or adequate*												

Figure 8. Changing the Obtained Values (Oj) in cells B4 and H4 from value 12 to 13 and from 10 to 11 respectively

	A	B	C	D	E	F	G	H	I	J	K	L	M
1	*Theoretical Cognitive Evolution Model - Memorization (Based in Chi-Square)*												
2													
3						**Observations**							**Average**
4	Obtained Values (Oj)	14	13	14	15	14	13	12	12	17	15		13,9
5	Expected Values (Ej)	16	16	16	16	16	16	16	16	16	16		
6	(Obtained-Expected)^2/Obtained	0,25	0,56	0,25	0,06	0,25	0,56	1,00	1,00	0,06	0,06		
7													
8													
9	Degrees of Fredom	9											
10	Error Value (alfa)	0,050	5%			$\chi^2 = \sum \frac{(o_j - e_j)^2}{e_j}$							
11													
12	*Chi-Square Value*	*4,0625*											
13	*Chi-Square Table Value*	*3,325*											
14							CONCLUSION						
15													
16	*Hypothesis to test*						H1 is true and H0 is disposable						
17	*H0 - The method is valid and adequate*												
18	*H1 - The method is not valid or adequate*												

Figure 9. Changing the Expected Value (Ej) to 16 and rising cells B4, C4 and H4 one value

As we can observe in Fig. 7, when the expected value is changed to 15, it turns into an unsustainable value. The value obtained through the evaluation function considerably exceeds the observed in the distribution table of the Chi-square. This situation was already expected, since as we can observe in Fig. 3 and Fig. 4, the slightly *Ej* value change anticipates that conclusion.

Maintaining all the structure and changing only the cells B4 and H4 one value each, the H_0 hypothesis is again true. We can then conclude hypothetically that the student can now achieve the level 15.

Changing all *Ej* values to level 16 and rising one value in cell B4, C4 and H4, the level 16 is now accepted as valid, making the hypothesis H_0 true, which means that the student, in theory, can achieve knowledge at this level.

A. Comparative analysis.

Observing Fig. 10, Fig. 11 and Fig. 12 and by analyzing the trace of the blue and green lines, in all the examples, we realize that in relation to the wrapping of the blue line around the reference line — the red line, which is the line that represents the *Ej* value — the closer they are, the higher is the probability of *Ej* be correct and, consequently the choice made by the GA will be most accurate in the choice of the KB level most adequate to the difficulty level that the evaluation function will return.

As for the green line on the chart, it follows in direct proportion the dephasing of the evaluation function.

In Fig. 10 we verify that the involvement of the blue line in relation to the red reference line is approximate, with the exceptions that are presented in to the referential X, in the peaks of points 7 and 9, respectively.

We will observe in Fig. 11 and Fig. 12 that these peaks will increase in direct proportion to the remoteness of the blue line in relation to red line.

In Fig. 11 we can observe that the dephasing between the blue line and the reference line — the red one — is accentuated. This happens because the expected value is not a viable value to fulfill the H_0 hypothesis.

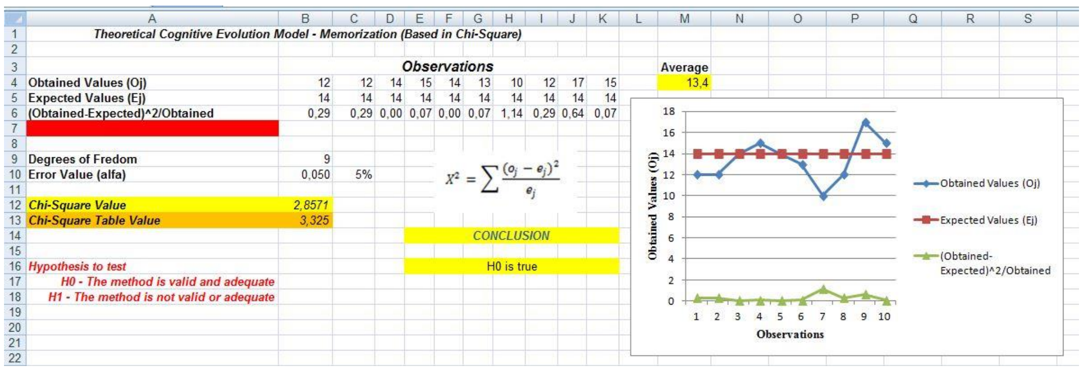


Figure 10. Comparative Analysis of Obtained Values (Oj) vs Expected Values (Ej) for Expected Value (Ej) of 14

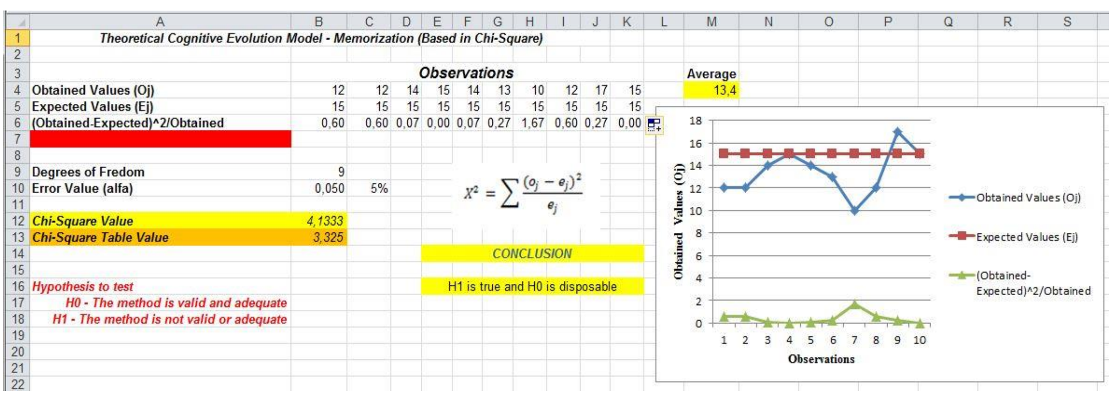


Figure 11. Comparative Analysis of Obtained Values (Oj) vs Expected Values (Ej) for Expected Value (Ej) of 15

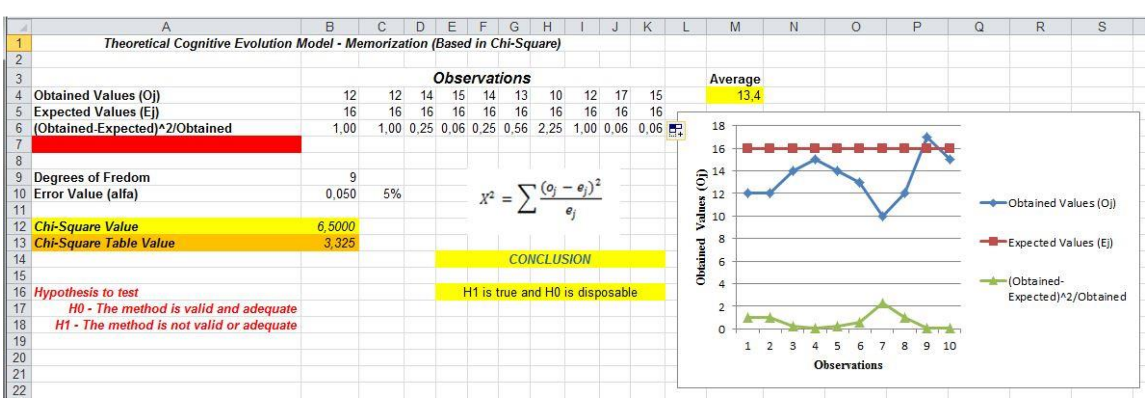


Figure 12. Comparative analysis of Obtained Values (Oj) vs Expected Values (Ej) for Expected Value (Ej) of 16

In the latter case — see Fig. 12, the spacing between the blue line in relation to the reference line — the red line, shows that the expected value are totally out of phase in relation to the possible cognitive reality. In relation to the green line, it becomes obvious a greater amplitude due to the fact that the difference between *Oj* and *Ej* be considerably higher.

By the analysis of the three previous examples — see Fig. 10, Fig. 11 and Fig. 12, we can infer that maintaining the *Oj* values unchanged, when the value *Ej* increases and diverts from the average values obtained in *Oj*, the involvement of the blue curve in relation to the red reference line becomes increasingly out of phase. This means that the expected values in *Ej* are not adequate to the obtained values in *Oj*.

In this sense there needs to be a correction to a more approximate value of the average value of *Oj*, to obtain a value of the evaluation function that allows the H_0 hypothesis to be true.

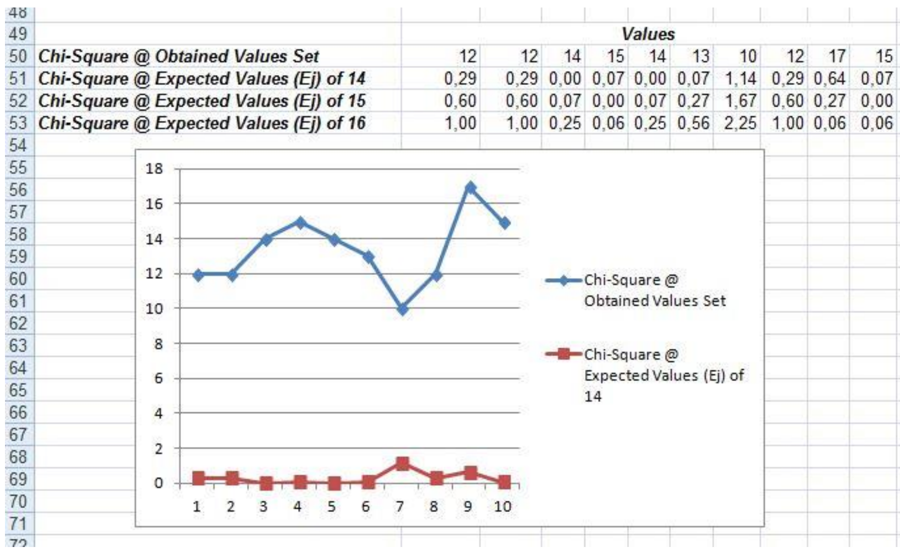


Figure 13. Comparative Analysis of Expected Values (Ej) of 14

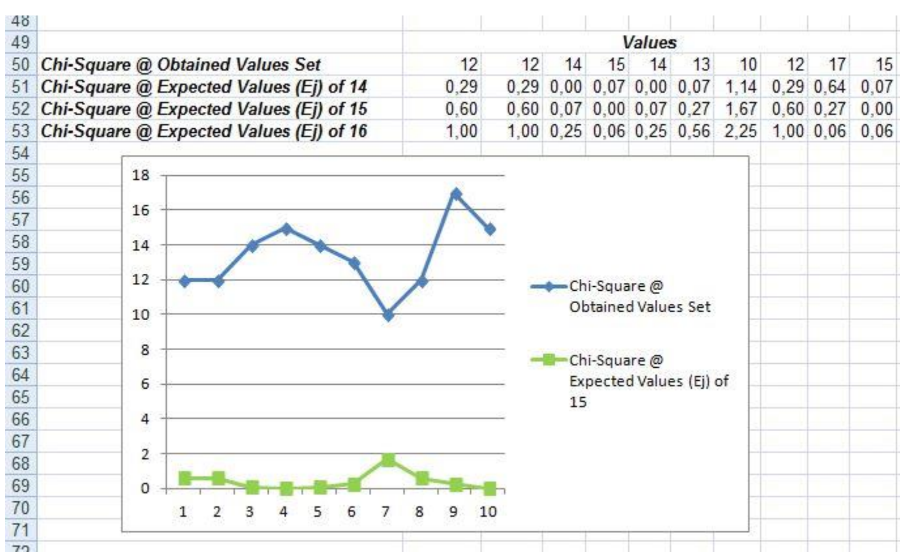


Figure 14. Comparative Analysis of Expected Values (Ej) of 15

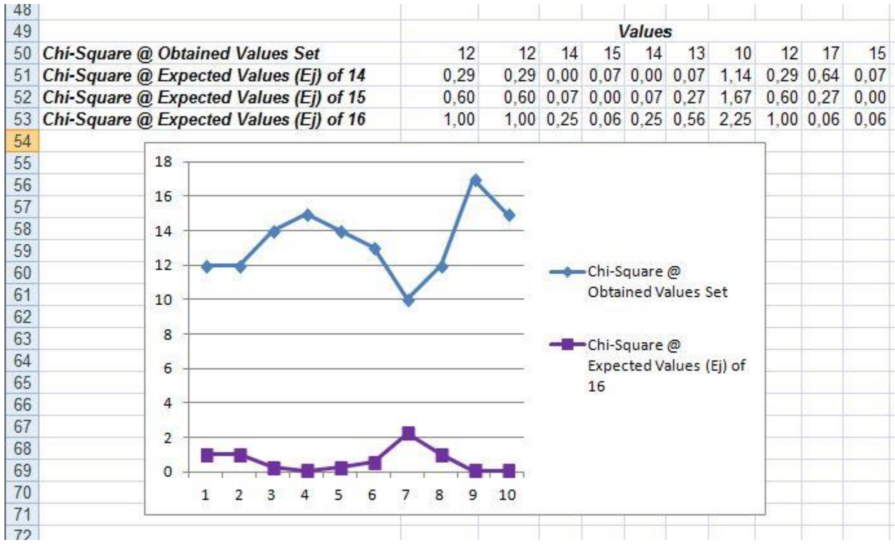


Figure 15. Comparative Analysis of Expected Values (Ej) of 16

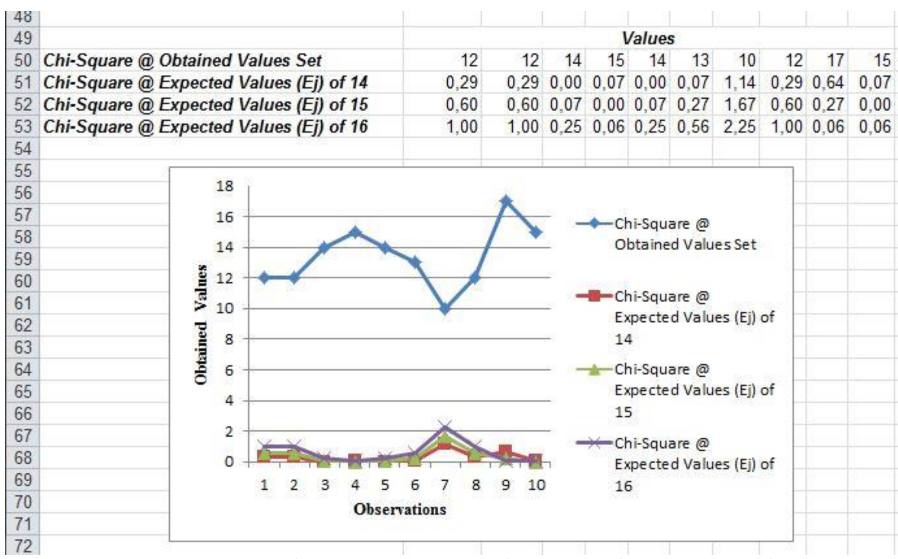


Figure 16. Comparative analysis (review) of Expected Values (Ej) of 14, 15 e 16 for the same set of Obtained Values (Oj)

When comparing Chi-square for the *Ej* of 14, 15 and 16, respectively — see Fig. 13, 14 and 15 — maintaining the same values of *Oj*, we can verify that the amplitudes of the evaluation function are considerable for *Ej* of value 15 and 16, respectively. It was an expected reaction since the values above 14 are not real for the present scenario — see Fig. 11 (Obtained Values). If we observe also the average value — see Fig. 11 — would be unreal, the assumption of values above 14 with an average of 13, 4.

By comparative analysis of the entire data set — see Fig. 16, we observe effectively that to the same *Oj* data set, comparatively, we can see a remarkable discrepancy of the *Oj* value of 10 for all *Ej* 's and, transversely, greater amplitude to values of *Ej* of 15 and 16.

In conclusion, and by the analysis of the data, done in this chapter, we may conclude that a small X^2 value indicate a good fit between the observed and the expected values. Large differences between observed and expected values result in a large value of X^2. Consequently, large values usually lead to the rejection of the H_0 hypothesis [9].

4. Conclusions and Future Work

The expected results, according to the simulations, allow us to conclude that the method will work, more that the acuity level imposed — margin of error (α) is extremely low, only 5 %.

In order to evaluate the proposed system, a class of students (21 children involved) has been divided randomly into two groups. One group uses the system under the control of the evaluation function and the GA, while the other follows the normal course. The tests will be performed during the current school year, after which we will get the final results. During this period, the structure proposed will suffer some modifications in order to improve the performance.

In the future, it will be taken into account the possibility of this solution to include the capacity to make several choices, regarding the KB selected, allowing the improvement of two or more cognitive profiles. We intend to use evaluation methods by computer trough the algorithm Cota-Groppo [10], using a new interface to communicate with the GA, and subsequently with the evaluation function, in order to introduce a higher accuracy in the results. The introduction of psychological states, such as emotional and affective responses [11] should also be considered in future work.

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