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Using children's search patterns to predict the quality of their creative problem solving

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Abstract

Purpose – The purpose of this paper is to propose a computational model that implicitly predict the children's creative quality of solutions by analyzing the query pattern on a problem-solving-based lesson.
Design/methodology/approach – A search task related to the competencies acquired in the classroom was applied to automatically measure children' creativity. A blind review process of the creative quality was developed of 255 primary school students' solutions.
Findings – While there are many creativity training programs that have proven effective, many of these programs require measuring creativity previously which involves time-consuming tasks conducted by experienced reviewers, i.e. far from primary school classroom dynamics. The authors have developed a model that predicts the creative quality of the given solution using the search queries pattern as input. This model has been used to predict the creative quality of 255 primary school students' solutions with 80 percent sensitivity.
Research limitations/implications – Although the research was conducted with just one search task, participants come from two different countries. Therefore, the authors hope that this model provides detection of non-creative solutions to enable prompt intervention and improve the creative quality of solutions.
Originality/value – This is the first implicit classification model of query pattern in order to predict the children' creative quality of solutions. This model is based on a conceptual relation between the concept association of creative thinking and query chain model of information search.

Keywords Elementary education, Information search behaviour, Creative thinking, Educational data mining, Children's search patterns, Query pattern

Paper type Research paper

1. Introduction

The increasing automation of everyday tasks and the progressive growth of available information make creative problem solving one of the most relevant skills of the twenty-first century. In this context, creativity and efficiency align to achieve a creative and efficient solution. However, students who are good at mathematics, science or language are not necessarily good at creative problem solving (OECD, 2014). Fortunately, creativity is not an innate ability but can be developed. There are many creativity training programs which have proven effective (Mansfield *et al.*, 1978; Scott *et al.*, 2004).

Creative problem solving demands an active process of searching for alternatives, i.e. information, to develop a novel and useful solution for a proposed challenge. Similarly, concept association skills have proven essential for the generation of creative ideas, since the greater the amount, diversity, originality and elaboration of associations, the better the opportunity for creative ideas to emerge (Mednick, 1962; Torrance, 1966, 1974; Torrance and Goff, 1990; Benedek and Neubauer, 2013).

Unfortunately, measuring creativity requires long procedures where experts on creativity have to evaluate it manually. Also, creativity is often explicitly measured – which tends to predispose individuals – through activities designed exclusively for the evaluation and thus, external to the learning process. We propose a computational model that implicitly predicts the children's creative quality of solutions by analyzing the query pattern on a problem-solving-based lesson.

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As we have seen, the tools to evaluate creativity use specific instruments that measure association skills in order to predict the creative potential. However, applying them is time-consuming and they are far from the reality of primary school classrooms. On the other hand, the process of searching for relevant information to solve problems has been widely studied (Jansen *et al.*, 2009; Kuiper *et al.*, 2005; Li and Belkin, 2008; Wu *et al.*, 2012; Hölscher and Strube, 2000; Fidel *et al.*, 1999) and the factors that influence the performance are known, such as previous knowledge, search experience, affects, type of tasks and others. This study aims to obtain indicators that predict creativity using primary school students' behavior when they perform search tasks to meet a challenge where associative skills are needed. In this way, we obtain a tool which is easy to implement in the classroom and we open the way to early detection, as well as to intervention in the event that low performance is predicted.

2. Related work

2.1 Creativity-driven problem-solving measurement tools

Creativity-driven problem solving can be seen as a process of understanding the problem and searching for alternatives that will be evaluated and applied. This process involves both creative and domain abilities (Amabile, 1983). Treffinger *et al.* (2003) have proposed and validated a creative problem-solving model that establishes a four-phase process: understand the challenge; generate ideas; prepare for the action; and plan the approach. This model has been applied in face-to-face, blended and online learning environments. All of them involve an intensive process of searching for alternatives or generating ideas that depend heavily on the individual's creative skills, mainly on associative and executive abilities.

Mednick defined creativity in terms of the Associative theory, where he proposed three ways to achieve creative ideas: serendipity, discovering something by chance during the search process through the occurrence of a trigger element; similarity, generating ideas that are close, by definition, to a trigger element; or mediation, achieving the association through a common element between the associated concepts and the trigger element. In any case, the emergence of creative ideas needs a trigger element that contributes to the concept association in the mind of individuals. Mednick proposed and validated an association model through the Remote Associates Test (RAT). This test has 30 sets of three independent words that have a common but remote association. Participants have 30–40 min to find the association for all the sets of words (Mednick, 1962).

Mednick's work contributed to the definition of the creative thinking process as the setting up of associated elements in new combinations that fulfill specific requirements of the problem or that are somehow useful to solve it. However, other authors studied the processes of generating creative ideas and did not find differences between creative and non-creative individuals in the associative hierarchies established by Mednick (Coney and Serna, 1995; Benedek and Neubauer, 2013). These discrepancies call into question the validity of RAT as a tool to predict creative potential.

On the other hand, one of the main instruments to measure creative potential is the Torrance Test of Creative Thinking (TTCT). The first versions of the TTCT (Torrance, 1966, 1974) relied on the characteristics of divergent thinking defined by Guilford *et al.* (1956, p. 1): flexibility, i.e. the number of different responses; fluency, i.e. the number of relevant responses; originality, i.e. the statistical rarity of the responses; and elaboration, i.e. the amount of detail in the responses. Even if the TTCT is a widely used instrument in different scenarios and has a high degree of creative prediction potential, its implementation has noticeable drawbacks: it requires experience using this tool, it is time-consuming both for reviewers and subjects (60 min), and it implies an excessive workload for participants, especially if they are primary school students.

2.2 Information search and creative solutions

Effective information search is one of the key competencies of the new digital literacy. Even so, most teenagers use web search engines, but are not aware of the strategies to find relevant information efficiently (Wu and Cai, 2016). Even more for children which have special requirements, strategies and preferences during information search tasks and search interfaces (Gossen *et al.*, 2011). A poor performance in this competency hinders obtaining creative solutions in unknown domains, because children are not always able to properly explore the search space.

In this sense, there are several factors that influence the efficient information search process. First, participants' literacy level, Kodagoda and Wong (2008) found that users with low literacy levels needed significantly more time to solve a search task than those with a higher level. Second, the tool design, Bateman *et al.* (2012) attributed the underperformance of participants to the low level of feedback from web search engines and they found higher effectiveness when a control panel was introduced with information about the performance achieved in the process. Similarly, Druin *et al.* (2009) studied the behavior of children aged between 7 and 11 when searching information on the web, and they concluded that the design of the search tools should facilitate query formulation and selection of useful and/or relevant information. Also, Gossen *et al.* (2011) studied the preferences and strategies of children and adults during search tasks, and they concluded that children have no significant preference by one particular search engine, but they are more explorative than adults. Third, the complexity of the task, Wu *et al.* classified tasks according to their cognitive complexity: remember, understand, apply, analyze, evaluate and create. The results of their work showed that users' interaction level with Google increases with the cognitive complexity of the task (Wu *et al.*, 2012). A complex task promotes a broader diversity of queries because its purpose is to acquire information from the web to solve a problem, i.e. informational queries (White and Druker, 2007; Broder, 2002; Jansen *et al.*, 2008). Other works distinguish two different contexts in the information search tasks: open, where users interact with a Web search engine provided with a wide variety of documents and they need effective strategies to find relevant information; and closed, where users query a specific search engine that retrieves information from a restricted and validated set of documents (Weber and Jaimes, 2011; Usta *et al.*, 2014). In this sense, children are more successful with the second environment because they do not always validate the information sources. Nevertheless, the open environment is richer than the closed one in terms of creativity.

3. A query-pattern-based predictive model

During the creative problem-solving process, people show their associative skills, mainly through actions undertaken during the information search phase. If the proposed problem is difficult enough, this search phase is more interactive (Wu *et al.*, 2012) and it, therefore, generates more complex and diverse search patterns. In order to promote exploratory search, it is important to adjust the problem complexity to participants' ability (Wildemuth and Freund, 2012). This type of searches is more likely to produce creative ideas through serendipity, similarity or mediation because they are oriented to achieving greater coverage in the analysis of results and to the promotion of intellectual development (White and Roth, 2009).

The model we present aims to obtain predictive indicators of creativity from the analysis of the search patterns and the formalization of creative attributes of flexibility, fluency, originality and elaboration. This formalization is mainly based on Torrance's model of creativity (Torrance, 1966, 1974). This model is useful to promote creativity, mainly if students show an implicit non-creative behavior.

Flexibility corresponds to the participants' capacity to generate a wide diversity of associations and depends on the diversity of the associations made. The formalization of this attribute for creativity is based on the Chain of Queries concept, i.e. each query is linked exactly to the previous query. Flexibility is measured by the average query reformulations made by participants, where a reformulation corresponds to any change made between a query issued at time t and one issued at time $t+1$.

We divide flexibility into two attributes: exact flexibility (F) and semantic flexibility (W). The former is calculated using the following formula:

$$F(Q^u) = \frac{\sum_{I=0}^{|Q^u|-1} c(q_i, q_{i+1})}{|Q^u|-1}, \tag{1}$$

where Q^u corresponds to the set of queries q_i issued by the participant u during the challenge resolution. Also, $c(\cdot,\cdot)$ determines if two adjacent queries are exactly the same:

$$c(q_i, q_{i+1}) = \begin{cases} 1, & \text{if} \quad q_i \neq q_{i+1} \\ 0, & \text{if} \quad q_i = q_{i+1} \end{cases}. \tag{2}$$

Semantic flexibility considers semantic similarities of queries. We calculate similarity using a semantic interpreter based on the Explicit Semantic Analysis (ESA) (Gabrilovich and Markovitch, 2007), which depends on the quantity k of concepts closest to the task and provides the similarity of these concepts regarding those used in each query. Therefore, semantic flexibility corresponds to the average of similarities among adjacent queries issued by the participant:

$$W(Q^u) = \frac{\sum_{I=0}^{|Q^u|-1} \kappa(q_i, q_{i+1})}{|Q^u|-1}, \tag{3}$$

where $k(\cdot,\cdot)$ calculates the similarity between two adjacent queries based on common concepts according to the ESA.

Fluency corresponds to the individuals' capacity to generate a large number of associations in a period of time. The formalization of this attribute for creativity is based on the frequency of queries issued by a participant and the time used to solve the problem or according to the total available time for the resolution. Our model considers both the relative fluency (f) (Equation (5)) and the total fluency (t):

$$f(Q^u) = \frac{|Q^u|}{T^u}, \tag{4}$$

where T^u is the effective time the participant has used to search for information. Conversely, the total time available to solve the challenge T is considered to calculate the total fluency:

$$f(Q^u) = \frac{|Q^u|}{T}. \tag{5}$$

These measures are the same when the participant needs all the available time to solve the challenge.

Originality is the participants' ability to generate globally novel associations. The formalization of this attribute is made through the relative frequency of the most repeated queries (M):

$$M(Q^u) = \frac{\max_f f(q, Q^u)}{|u(Q^u)|}, \tag{6}$$

where $f(q, Q^u)$ is the set of all frequencies of queries issued by the user and $u(Q^u)$ is the subset of unique queries within Q^u. Likewise, we obtain the minimum originality:

$$M(Q^u) = \frac{\min_f f(q,\ Q^u)}{|u(Q^u)|}. \tag{7}$$

In addition, originality is characterized by the average distance between each of the queries regarding the challenge definition n_s (Equation (8)), which is calculated through the semantic interpreter and depends on the quantity k of the concepts closest to the task:

$$O(Q^u) = \frac{\sum_{i=0}^{|Q^u|} \kappa(q_i, n_s)}{|Q^u|}. \tag{8}$$

This property describes the originality of queries in relation to the proposed problem.

Elaboration is the participants' capacity to provide ideas and solutions in great detail and it depends on their expressiveness. The formalization of this attribute is calculated through the variations of issued lengths (L):

$$L(Q^u) = \mathrm{var}[long(q_1), \ldots, long(q_i)] \forall q_i \in Q^u, \tag{9}$$

where *long* (·) calculates the length of each query issued by the user. Likewise, the average of the lengths of queries issued is calculated (l):

$$l(Q^u) = \frac{\sum_{i=0}^{|Q^u|} long(q_i)}{|Q^u|}. \tag{10}$$

We evaluate each query made by participants in the challenge through these attributes, used in several widely applied instruments to measure creativity (Equation (11)). The set of queries Q^u that each participant performs during a given challenge (i.e. information need n_s) models the associative strategy used to solve the problem, where the participant progresses, query by query, toward the elaboration of a solution S_u (Equation (12)):

$$Q^u(n_s) = [(q_1, t_1), (q_2, t_2), \ldots, (q_n, t_n)] \forall q_i \in Q^u, \tag{11}$$

$$h_u^*(n_s) = S^u(q_i, t_i | n_s) \therefore u \in U \wedge q_i \in Q^u. \tag{12}$$

With the aim of evaluating the predictive capacity of these attributes in the search for creative solutions, we performed an experiment with more than 200 participants from Spain and Chile. Details are described in the following sections.

4. Methods

We have conducted an experiment to analyze the students' search behavior and then followed a quantitative approach to propose a user model to classify students' solutions in terms of creativity. We have extracted the user behavior from the search interface to automatically predict the creative quality of students' solutions.

4.1 Participants

The experiment was conducted at two schools, one located in Spain and the other one in Chile, with the collaboration of teachers from each school. A total of 225 participants aged from 10 to 12 took part in the experiment, 90 of them at the Spanish school (52 percent male and 48 percent female) and 135 at the Chilean school (46 percent male and

54 percent female). All of them had their legal guardian's signed informed consent. However, none of the materials used can be considered sensitive or offensive (the topic is how to reduce energy consumption, as we describe later). Almost all (97 percent) the participants that started the challenge achieved a valid solution, i.e. they managed to send a non-null solution within the deadline, performing at least one query. Therefore, 3 percent of the participants were discarded since it was not possible to establish a creativity evaluation based on their queries.

4.2 *Apparatus and materials*

Both in Spain and Chile, we used classrooms equipped with personal computers to carry out the experiment. Participants used web browsers to connect to the challenge resolution framework (CRF) web application, developed specifically during this study. The CRF registers actions performed by participants during the information search process to solve a problem. Figure 1 shows the interface of challenges, where active challenges are shown in green and pending challenges are in blue. Figure 2 shows the information search interface with the library to store relevant papers and the complete description of the challenge. We used Bing search engine's Application Programming Interface from the search interface of the CRF, designed *ad hoc* for children and results are presented in the search interface. The solution interface is shown in Figure 3, where participants write their solution to the challenge and can consult the library built during the search process. Thanks to the CRF, we can register queries issued by participants and they are analyzed using the model described above.

4.3 *Procedure*

The principal investigator carried out the experiment using the CRF web application in a face-to-face session in Spain, and a virtual session in Chile. In both cases, a teacher from the school was present to provide the general instructions. In each session, students were grouped by course and their accounts were activated in the CRF for the session. Students in Chile and Spain were similar in age (mean: 12 years old) and gender (mean: 50 percent of female). In the case of Chile, schools were public, whilst Spanish schools were semi-public.

Participants had 35 min to solve the challenge whose main objective was: "to reduce the money spent on energy in your city's homes."

Figure 1.
Challenges interface: pending (blue) and active (green)

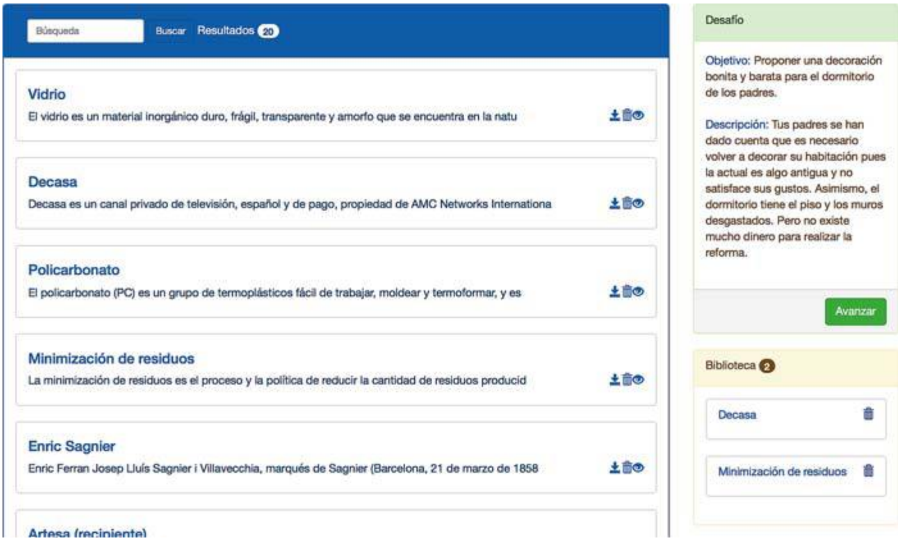

Figure 2.
Information search interface: results (blue), challenge (green) and library (yellow)

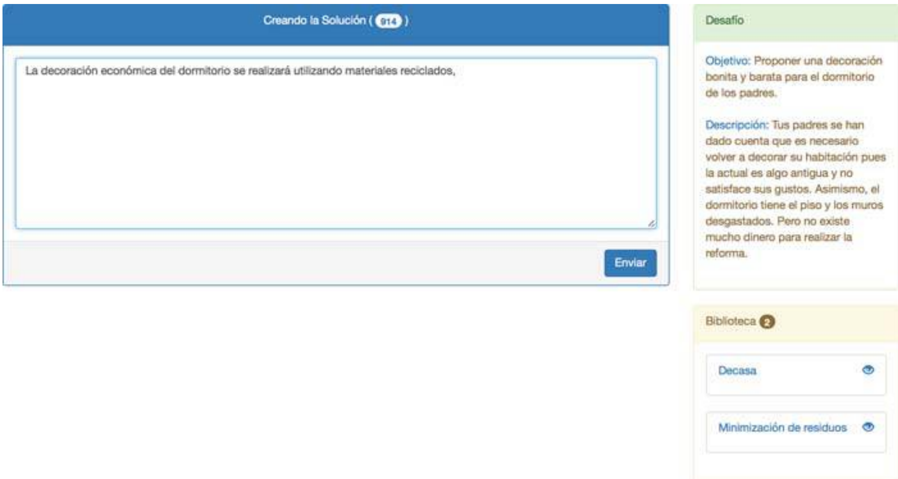

Figure 3.
Solutions interface: solution (blue), challenge (green) and library (yellow)

4.4 Ground truth definition through a creative solutions assessment

A group of reviewers evaluated the quality of the solutions issued by participants. They were selected according to the following criteria: knowledge of the problem area; experience in creativity training; and experience in the classroom. Three reviewers were selected with medium-high to high levels in one of these variables. One of them is a researcher in the field of energy consumption, another one is an academic with experience in creativity training and the last one is a teacher at the primary and secondary school from Chile.

Participants' solutions were shown sequentially to reviewers, randomly selected from the valid set of data. Reviewers, without knowing the author of each solution, analyzed each of the eight sub-dimensions of an evaluation rubric on creative ideas. This metric was developed from a detailed study of the state of the art on evaluation methods of creative ideas and products developed in the research of Dean and Hender (2006) and which has shown a strong level of inter-reviewer reliability (κ agreement, 0.86).

An average of the three reviewers' evaluations was obtained as a result of this process and each solution was classified as creative or not depending on whether the result is greater than a cut point α relative to the maximum possible mark.

4.5 Query-pattern-based model assessment

The evaluation of the model quality is carried out in three consecutive phases: determine the settings of creative attributes that provide the best performance, obtain the appropriate amount of concepts to define the queries depending on the task, and establish the learning algorithm that best fits the proposed model of creative-query associations.

The first phase is achieved through the design of 15 different settings of the model based on the possible combinations of the formalizations of the creative attributes: flexibility (*WF*), fluency (*ft*), originality (*MmO*) and elaboration (*Ll*). This determines the setting that provides the best performance detecting the participants' creative potential. With these settings as a base, we developed a cross-validation schema using R. We took ten divisions of the data set and repeated the evaluation for each division ten times, using Decision Trees (rpart) as the baseline algorithm and fixing the parameter k at 5 and α at 55 percent. For each running instance of evaluation, we obtained: the sensitivity or the relation of correct classification of positive instances; the specificity, or the relation of correct classification of negative instances; and ROC curve, or the relation between previous metrics. Based on the greater space value under the curve and the sensitivity, this evaluation schema provides the optimal configuration of attributes. This setting will be used as a base for the evaluation of the parameter k.

The second phase on the impact of the number of concepts (k) used in the definition building, both of the tasks and the queries, considered the configuration that provided the best performance from the first phase. Using Decision Trees (rpart) as the baseline algorithm and fixing the parameter α at 55 percent, the value of k varies in the range [5, 25] with a step of 5. The evaluation was carried out as in the previous phase, with a 10 division cross-validation, ten repetitions.

For the last phase, a more thorough cross-validation was applied in order to determine the generalization capacity achieved by the model setting obtained in the two previous phases: creative attributes and the number of concepts close to the task. With this purpose, we applied the leave-one-out validation model that divides the data set into $N-1$ partitions, using $n-1$ instances in each partition to train the model and one instance for the evaluation. The generalization capacity was measured applying the creative-query association model to four supervised classification algorithms that represent a wide variety of learning models: Decision Trees (tree), Naive Bayes, support vector machines (SVM) and random forests.

Finally, we obtained the optimal configuration of the model of creative-query associations to predict the creative potential that participants showed when solving a challenge. Similarly, we obtained a classification algorithm that interprets the formulation of creative variables proposed in the model.

5. Analysis

Participants who submitted valid solutions issued a total of 2,358 queries, distributed equally among male (51 percent) and female (49 percent). However, 15 percent of them were empty after word processing and were discarded, so 85 percent of them were taken into consideration. Issued queries had an average of 4.2 words. Females issued an average of 4.5 words (with a standard deviation of 2.7 and a maximum of 16) per query, while men's average number of words per query was 4.5 (with a standard deviation of 2.7 and a maximum of 18). These values are higher than those reported in an educational context, where the average length of queries was 2.16 words (Usta *et al.*, 2014). This shows how the complexity of the task was appropriately defined and offers greater opportunities for the query analysis.

5.1 Semantic analysis

We generated the semantic representation of queries performed by participants and the task used in the experiment with the schema proposed in Gabrilovich and Markovitch (2007). This schema relies on the $T[w, c]$ matrix that relates all the articles (concepts) of the Spanish Wikipedia (to March 18, 2015) with all the words contained therein. However, due to the large number of articles, we only considered those with a description of 400 words or more. During the Wikipedia articles processing, the following filters were applied to discard those terms that do not contribute to the word semantics: transform words to lowercase, remove stop words, remove digits and remove punctuation marks. After this process, 66,986 words and 450 concepts comprise the matrix of semantic interpretation, where each $T[w, c]$ cell determines the relation between the word w and the concept c, and the row $T[w]$ corresponds to the definition of the word w according to all the concepts.

The task n_s has a subset of most relevant concepts Cr and the definition of the query considers only k of these concepts. For example, if the most relevant concepts for the query, in increasing order, are: "Automóviles" (cars), "Consumo" (consumption), "Energía" (energy) and "Cambio Climático" (climate change); then, the definition of the query is formulated based on the relation between each word in it and k of these concepts. Therefore, the definition of the query in the space of states depends on the information need n_s for which it has been issued. The value k has been used in the evaluation of the proposed model to determine the impact of the number of concepts on the model's performance.

6. Results

In order to find the optimal set of attributes for our creative queries association model we first analyzed each of them separately. Table I shows that all of them achieve good results classifying positive instances (Sens.) in contrast to a poor classification of negative instances (Spec.). Next, we analyzed all combinations of the attributes. Table II shows the results obtained combining pairs of creative variables where there is not a significant improvement compared to the independent settings. However, the combination between fluency (*ft*) and elaboration (*Ll*) provides better results classifying negative instances, balancing the model's overall performance. Table III shows the remaining model settings. The combination of flexibility (*WF*), fluency (*ft*) and originality (*MmO*) is remarkable, which reaches the best

	Experiments: individual			
Metrics	*WF* (%)	*ft* (%)	*MmO* (%)	*Ll* (%)
ROC	60.3	58.2	57.2	60.9
Sensibility	76.3	81.1	76.9	73.6
Specificity	30.8	21.8	34.8	38.7

Table I. Evaluation of individual creative attributes

	Experiments: pairs					
Metrics	*WF* + *ft* (%)	*WF* + *MmO* (%)	*WF* + *Ll* (%)	*ft* + *MmO* (%)	*ft* + *Ll* (%)	*MmO* + *Ll* (%)
ROC	59.0	56.5	60.3	53.5	60.7	56.8
Sensibility	78.0	77.8	76.1	82.9	73.5	75.5
Specificity	31.5	29.6	33.1	22.4	38.8	29.9

Table II. Evaluation of the creative attributes in pairs overall performance with a correct classification of positive instances higher than 70 percent. Therefore, we used this configuration in the following evaluation phases.

Table IV shows the results obtained using the configuration of flexibility (*WF*), fluency (*ft*) and originality (*MmO*) with different *k* values. The performance achieved is stable, regardless of the value of *k*. However, when the number of concepts used in the development of query definitions increases, the expressiveness of those definitions increases as well. Consequently, this contributes to improving the relationship of negative instances classification.

Table V shows the results of the third analysis, where a detailed validation process leads to low detection of negative instances in favor of the positive ones, both with Decision Trees and SVM. Even so, the Decision Tree algorithm has learnt a positive model which only recognizes new instances as creative (0 percent in Table V). The Naive Bayes and random forests provide a more balanced performance between sensitiveness and specificity, which may be due to the intrinsic attributes of both learning models: Bayes Theory and Bagging.

Finally, Table VI shows the results obtained when applying the diversity of query model (DoQ) proposed by the authors in a previous work (Olivares-Rodríguez and Guenaga, 2015) to the data set obtained with the CRF and compares it with the model proposed in this work (FoC). As can be seen, the new model outperforms each of the metrics used in the DoQ model (Olivares-Rodríguez and Guenaga, 2015).

Table III. Evaluation of all the creative attributes combined

	Experiments: all				
Metrics	*WF* + *ft* + *MmO* + *Ll* (%)	*WF* + *ft* + *MmO* (%)	*WF* + *ft* + *Ll* (%)	*WF* + *MmO* + *Ll* (%)	*ft* + *MmO* + *Ll* (%)
ROC	56.3	63.9	62.1	58.3	56.4
Sensibility	71.9	71.8	71.8	77.4	83.2
Specificity	34.0	43.7	41.2	46.2	23.7

Table IV. Evaluation of the number of concepts close to the task that was used

	k-concepts				
Metrics	5 (%)	10 (%)	15 (%)	20 (%)	25 (%)
ROC	63.9	65.3	61.8	64.7	65.7
Sensibility	71.8	71.6	73.9	69.2	67.3
Specificity	43.7	41.2	36.2	45.0	45.0

Table V. Evaluation of the different learning algorithms

	Algorithms			
Metrics	Tree (%)	NB (%)	SVM (%)	RF (%)
ROC	85.3	64.1	58.8	63.7
Sensibility	80.4	47.1	89.1	80.4
Specificity	0.0	775	21.2	43.8

Table VI. Evaluation of the different user's models

	User's model	
Metrics	DoQ (%)	FoC (%)
ROC	52.9	63.7
Sensibility	70.2	80.4
Specificity	37.5	43.8

7. Discussion

The results show that the combination of flexibility, fluency and originality attributes provides a higher balance in the performance of classifiers, i.e. a better relationship between the classification of negative and positive instances. Furthermore, integrating the elaboration attribute in the model reduces the performance of classifiers in the prediction of negative instances. This means that the length of queries used to formalize the elaboration has proved a noisy attribute when classifying creative and non-creative solutions as was observed in previous work related to search effectiveness. This could be due to the age barrier, causing students in the sample to experience difficulties when they deal with query formulation during the information search task.

In spite of the good results obtained, there are some issues that could be addressed in the future. On the one hand, during the application of the CRF participants generate a great amount of data (queries, clicks, navigation, information selection, etc.), but the proposed model only considers participants' queries, leaving aside the analysis of remaining data for subsequent models. On the other hand, the semantic analysis used in this model is based on concepts extracted from Wikipedia's articles with more than 400 words. The cross-country data acquisition provides diverse to search pattern; however, a higher number of search tasks should be considered in the future to prove model robustness. The inclusion of more concepts could increase the expressiveness of definitions and impact the overall performance of the model. Finally, we could also evaluate indicators of the TTCT which have not been included in this work due to their high level of abstraction (note that this model relies on flexibility, fluency, originality, and elaboration of queries). A study of the existing attributes in the queries pattern that could be correlated with those indicators should be conducted. Finally, a study focused on influence of age on search patterns in a creative context should be conducted, considering children, middle school students and adults as in Bilal's work (Bilal and Kirby, 2001, 2002).

8. Conclusions and outlook

We live in a society where the huge amount of available information can be both a threat and an opportunity if we are able to develop efficient search processes for creative problem solving. In this context, the availability of a tool capable of evaluating these processes automatically opens the way to a large number of scenarios. At the educational level, it allows the development of technologically improved learning platforms capable of detecting outliers (both at the upper and bottom ends) in order to develop an early and effective intervention plan. At the psychological level, it allows to measure and evaluate not only creative solutions but also the problem-solving process, which leads to a better understanding of the information processing and filtering. At the sociological level, the automatic evaluation of millions of search patterns within a platform provides a better comprehension of the information dissemination and curation. Even if there are many open issues in this area, the prediction of the creative quality of alternative solutions based on the search pattern offers a large number of research possibilities in several areas. This work aims to be an initial step in the long journey toward the automatic evaluation of creativity in the future.

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