Analysis of the Emotions Experienced by Learning Greedy Algorithms with Augmented Reality

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***Abstract*—Students have difficulties in understanding algorithm subjects, in particular how the source code of algorithms proceeds to solve problems. This article presents an augmented reality tool intended to assist in learning greedy algorithms. Students use their smartphone's camera to focus the source code of Dijkstra's algorithm as written on paper, and the tool shows how the algorithm works. An experience was conducted in the classroom to assess students' emotions and knowledge level. The results show that positive emotions experienced by students were almost twice as intense as negative ones. Despite the complexity of the task (i.e. understanding Dijkstra's algorithm), the level of enjoyment of students was continuous during the experience. However, the anxiety experienced by students was the double than at the beginning.**

Keywords— Emotions, learning, Augmented reality, Greedy Algorithm.

I. Introduction

In algorithm design subjects of university computer science degrees, the development of algorithms that solve optimization problems is usually studied. In this educational context, learning greedy algorithms is one of the most complex topics for the student, not being able to translate into source code the elements of their development (i.e., set of candidates, selection function, feasibility function, objective function) [1]. This difficulty may affect the emotional state of students and cause them to become discouraged during the learning process. Motivation and emotions in learning play a fundamental role since they influence memory and logical reasoning and help improve attention [2]. Today, neuroscience research helps us in understanding how the brain works and the influence and importance of emotions to improve learning [3,4]. Along with this, if a student is not predisposed to learn, or he/she experiences strong negative emotions, it is unlikely that he/she will be able to achieve his/her full potential. Furthermore, learning is characterized as a cognitive and motivational process [5], where emotions may affect both the intrinsic and extrinsic motivation of the student [6,7].

Not only emotions can influence learning outcomes. The use of new technologies plays a relevant role in learning [8]. Specifically, augmented reality (AR) technology may improve learning performance [9] and constitutes a technology option with great potential and effectiveness to activate positive emotions in students [10]. Augmented reality not only provides immersive experiences of visibility or observation [11-13], but it may also contribute to student's feeling of greater satisfaction [14], improved usability [15] and reduction of his/her cognitive load [16] in the use of technological tools during the learning process. Augmented reality technologies have been applied to programming learning at different educational levels, showing satisfactory results: from early ages [17,18], high school and university students [19] to professional adults [20], being applied mainly through teaching methodologies based on gamification [21,22] and collaborative learning [23]. The objective of this work is to conduct an exploratory study of the advancement of knowledge and the emotions that students experience while they study greedy algorithms using augmented reality technologies. An experience was conducted in a classroom where students used an augmented reality tool on their smartphones, called RA-AVD (Realidad Aumentada – Algoritmo Voraz de Dijkstra, in English Augmented Reality – Dijkstra's Greedy Algorithm), along with paper notes provided by the teacher.

II. Methodology

A. *Educational objective and context*

The objective of the experience is to assess the level of knowledge and the positive and negative emotions that students experience by using the RA-AVD tool in solving optimization problem. The experience is conducted in the context of the Computer Science Degree at the Salesian Polytechnic University of Ecuador, specifically in the area of Data Structures. At some point in this subject, students have to learn and develop greedy algorithms. In particular, they must understand Dijkstra's algorithm [24], which solves a classic graph problem: determining the minimum length path from a source node to the rest of the nodes in the graph. Students participated voluntarily and they had no previous contact or knowledge about greedy algorithms, although they knew how to program and have basic knowledge of the Java programming language.

B. *Variables and measurement instruments*

The variables measured were the emotions experienced by the students and the level of knowledge they acquired after the experience. The level of knowledge is measured by a knowledge test on the behavior of Dijkstra's algorithm. The test was formed by 5 multiple-choice questions where each question was scored with maximum 2 points.

The instrument used to measure emotions was AEQ (Achievement Emotions Questionnaire), which is a consistent and validated scale in the educational context [25]. Taking into account the principles of neuroeducation [26], the emotional variables to be measured can be classified into two types: 1) activation emotions, which are the emotions that produce a higher degree of agitation (fear, anxiety, anger, etc.) and 2) deactivation emotions, which produce lower agitation (depression, calm, boredom, etc.). In addition, these emotions can be classified by the positive (pleasant sensation) or negative impact (unpleasant or uncomfortable sensation) that they produce on participants. Overall, up to four classes of emotions could be identified.

The AEQ scale measures these emotions by offering a series of statements about the participant's emotional state and students must assess the degree to which they describe their

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emotions and feelings. Each statement is rated in a Likert scale, which ranges from very little (value 1) to extremely (value 5). In Table I, the variables of emotions measured with AEQ are detailed (the number in parentheses corresponds to the total of items to be assessed for that emotion). Note that the test only addresses three kinds of emotions and that it consists of 75 items which measure 8 emotions.

TABLE I. MEASURED VARIABLES OF EMOTIONS AND THE NUMBER OF ITEMS

Emotion	**Activation**	
	Activation	***Deactivation***
Positive	Enjoyment (10) Hope (6) Pride (6)	
Negative	Anger (9) Anxiety (11) Embarrassment (11)	Hopelessness (11) Boredom (11)

AEQ scale is organized so that students assess at the end of the session their emotional state at three different times:

1) Before starting the learning task: the student assesses how he/she feels right at the beginning of the experience.

2) During the task: the student assesses how he/she feels while doing the learning task.

3) After the Task: the student rates how he/she feels after completing the experience.

Finally, the opinion of participants about the experience was collected by asking some of them their opinion in a short interview.

C. Phases

In the first phase, students attended at a laboratory and they received on printed sheets the markers to present the information with augmented reality. These sheets contained the Java source code for Dijkstra's algorithm.

Subsequently, students downloaded the application to their mobile devices and a brief explanation was given about the task to be carried out (for 10 minutes), which consisted of reading and interpreting the source code that appeared on the sheets provided.

While reading the Java code on paper, students could use the mobile to focus parts of the code and receive assistance from the application. This phase lasted 30 minutes.

Once this phase was finished, the students proceeded to carry out the evaluation of acquired knowledge and they measured the emotions experienced before, during and after the learning task, using 15 minutes for this. The whole experience was organized in a single session.

III. App design

RA-AVD is a tool created for learning Dijkstra's algorithm. The use of the tool is based on the following idea. The student uses the teacher's notes where the Java code that implements Dijkstra's algorithm is shown (for the tool to recognize it, it has to be a specific source code). When the student has doubts about how the code solves the problem, he/she uses the tool, focusing on the source code with his/her mobile. At that point, the tool shows the source code that the student is viewing on paper, augmenting it with comments and explanations in order to understand how it works. If the student focuses the source code where the graph is declared, RA-AVD tool draws the graph on the mobile's screen (see Figure 1). In summary, the student can read code in the sheets (a static description of the solution) and can watch an animation of the algorithm on the mobile (a dynamic demonstration of the solution).

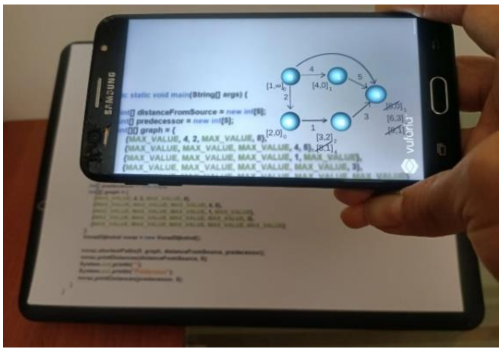

Fig. 1. Extension of the source code with the visualization of the graph detected by means of augmented reality.

The tool has a user interface that allows to control step by step the execution of the algorithm, obtaining a display of its execution trace, as in a debugger (see Figure 2). This trace screen shows the graph declared in the source code at the top and the trace table along with the step-by-step execution controls below (see Figure 2).

Figure 2 shows the trace in an intermediate state to calculate the minimum paths from node 0 to the other nodes. Notice that some nodes present a label formed by brackets in the form of $[A,B]_N$, where A is the distance of the path from the source node to the node, B is the predecessor node from that path and N is the resolution stage number. The algorithm solves the problem in stages, in such a way that at each stage it analyzes possible new paths between the source node and each remaining node, recording a new path if it is shorter than the current path. Therefore, these labels are dynamically generated as tracing progresses, and they are replaced every time the algorithm finds a shorter path. In this case, the path that partially expresses the bracket label is discarded (by displaying a horizontal line that crosses it out) and a new label is shown by the node, representing the new path.

An example may assist in better understanding this notation. In Figure 2 we can see that node 3 has the label $[8,1]_4$ with a crossing line, which means:

- Number 8: length of the path from source node to node 3 (labeled node).
- Number 1: node predecessor to node 3 in the path from the source node.
- The subscript 4: step or stage in the solution construction process.
- Strikethrough label (crossing line): it means that the path denoted by that label is discarded. Node 3 has two labels since, at that time, the algorithm had found two alternative paths (namely, $[3,2]_2$ and $[8,1]_4$). The path with a longer distance from the source to node 3 was discarded. In this case, the label $[8,1]_4$, with distance 8, was discarded since the other path was shorter, with length 3.

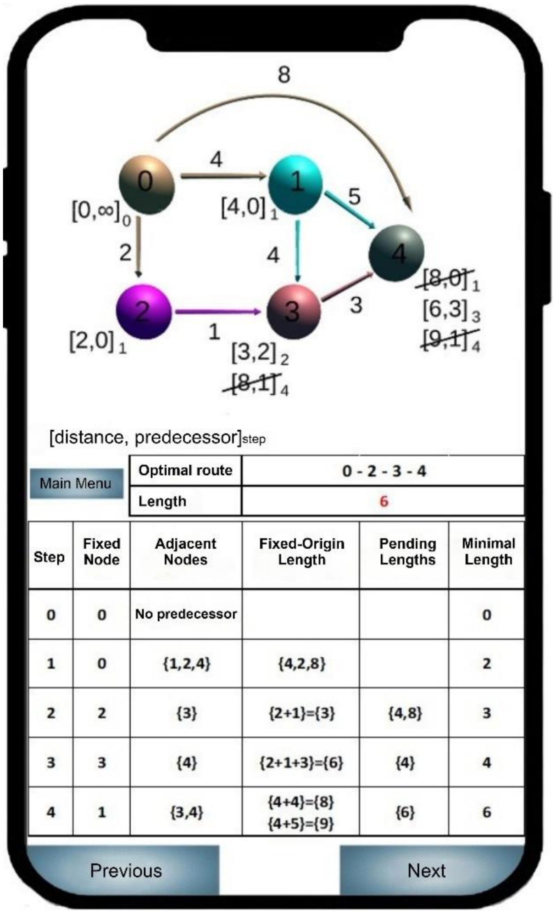

Fig. 2. Running the algorithm step-by-step in RA-AVD

The trace table has the following columns (see Figure 2):

- Step: number of the stage of construction of the solution.
- Fixed node: the candidate node selected by the selection function at each stage (of all the candidate nodes, the one with the shortest path length from the source node is selected).
- Adjacent nodes: the nodes adjacent to the selected node.
- Fixed-origin length: for each adjacent node, it indicates its distance from the source node.
- Pending lengths: the lengths of the paths from the source node that have not been selected so far. It is made up of values from the column "Fixed Origin Length" that have not been selected.
- Minimum length: the shortest length of the lengths of the adjacent nodes of the fixed node and the pending lengths.

Let's see an example to better understand the meaning of these columns (note that the source node is 0). Step 0 indicates the initial state. In step 1, the algorithm marks the origin node 0 as a fixed node (in the first step the origin node itself is chosen as the fixed node), and determines the adjacent nodes, which are nodes 1, 2 and 4, writing them down in the "Adjacent Nodes" column. Next, the algorithm determines the distance from these nodes to the origin, whose lengths are 4, 2 and 8 respectively, and write them down in the column "Fixed-Origin Length". Subsequently, the algorithm selects the smallest of these paths (4, 2 and 8), in this case the smallest path is 2, and its corresponding node (node 2), so it is marked as a fixed node for the next stage (step 2). That would be the end of the stage, hence a new stage would start until the minimal path to all nodes is reached.

At the top of the trace table, the "Optimal route" and "Length" fields show, at each stage, the optimal path and its length respectively for the selected, fixed node. Initially, all nodes are painted in one color and as they are processed in the construction stages their color changes to show which part of the graph is being processed.

IV. Results

This section presents the statistical analysis of the data obtained during the experience, in which 18 students aged 19 to 22 participated. Eleven students (61.1%) were men and 7 (38.9%) were women. The analysis was performed with the IBM SPSS tool and the Pandas Matplotlib library in Phyton.x.

A. *Acquired knowledge*

Table II shows the level of knowledge acquired by the students after the experience. Students had neither previous contact nor knowledge about greedy algorithms at the beginning of the experience. However, at the end of experience they obtained an average score close to 7 out of 10 (specifically 6.95). Table II displays the mean scores per question (maximum 2 points per question) and the total mean. It should be noted that half of the students in the group (50.5%) obtained a score higher than 8, the maximum score being 10 and the lowest 3. Furthermore, we can see that in three of the five questions students scored more than 1.7 out of 2 points. Therefore, that the level of knowledge is quite satisfactory.

TABLE II. Knowledge evaluation questionnaire and scores obtained by questions

Number	Statement of the task or question	$\bar{x}$
1	Select the distance of two adjacent nodes when they are equal	1.72
2	Indicate the sequence of edges that Dijkstra would calculate from the origin to node X	1.78
3	Find the shortest path from vertex X to vertex Y	0.56
4	Identify which is the predecessor node of node X in the graph.	1.89
5	Starting from the origin node, what would be the predecessor node Not selected for node X in step N.	1.00
Total		**6.95**

B. *Positive activation emotions*

Figure 3 shows the mean of the positive emotions (enjoyment, hope and pride) valued by the students at three different times: before, during and after the experience of use of the tool. Not all emotions were measured at all times. For example, measuring proud about accomplishment in the task does not make sense before having done it, or there is no point in measuring the students' level of hope about what they will learn once they had learnt it. Therefore, in Figure 3 not all the positive variables appear at all times.

We can see that the average enjoyment remains roughly the same throughout the experience (between 3.72 and 3.70). We also found out that hope decreased in students while they did the task from 4.13 to 3.96 (i.e. 4.12%), and that pride felt once students finished the task decreased from 3.86 down to 3.67 (4.92%).

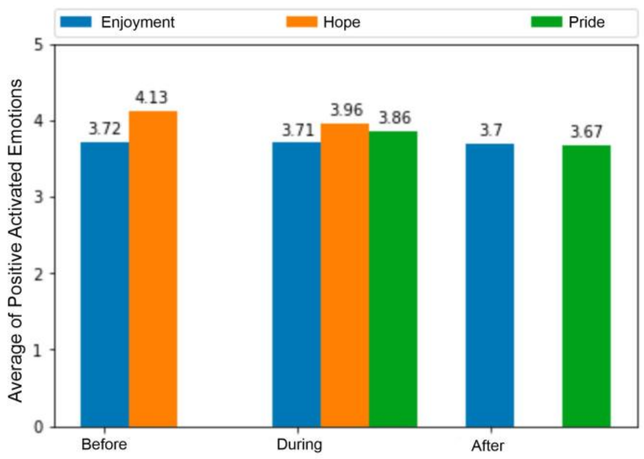

Fig. 3. Positive activation emotions

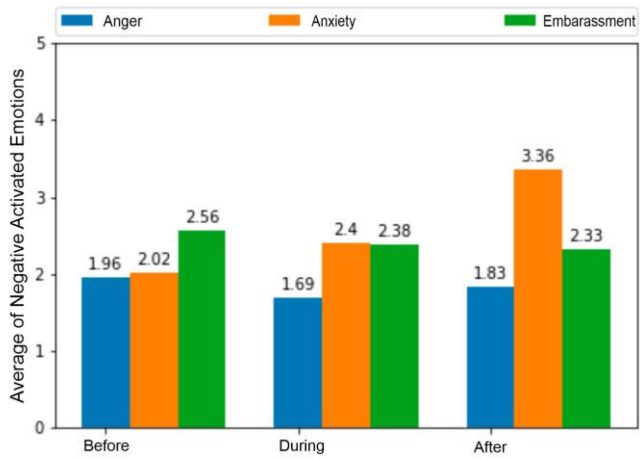

Fig. 4. Negative activation emotions

The fact that enjoyment remained constant can be interpreted as a favorable symptom, since the learning task entailed concepts that were new and difficult to understand for students, and despite this fact they did not stop enjoying during learning. The authors wonder whether the use of AR may have been the reason of keeping constant the levels of enjoyment. In relation to this feeling of enjoyment, it should be noted that item 110 of the AEQ questionnaire ("I study more than necessary because I enjoy it a lot") obtained the lowest score with an average of 2.89, which indicates that the student is not interested in studying more than strictly necessary. Note that we numbered the items same way as the AEQ questionnaire. Rather, it seems that they were interested in acquiring new knowledge that seems significant to them, judging by the evaluation of question 139 ("I enjoy acquiring new knowledge"), which obtained the highest score (4.33 out of 5).

Regarding the decrease in pride, it should be noted that the highest score of the questions of the AEQ questionnaire to measure this emotion is item 135 ("When I excel in my work I feel proud"), which had an average of 4.00 out of 5. Thus, students value the work they do and feel proud of it. It is possible that they did not value the task they had to do (analyzing Dijkstra's algorithm) as an interesting task and this could have caused that pride decreased at the end of the experience.

C. *Negative activation emotions*

In relation to these emotions we could observe that the average anger decreased during learning and increased when the task was finished by 7.65% (see Figure 4). On the other hand, the level of anxiety increased notably from the beginning of the experience, being 15.83% higher during the experience and 28.5% at the end of it (Figure 4).

It was also observed that students felt worried and anguished about having to deal with too many study materials and about having little time, since the items of the AEQ questionnaire related to this aspect of anxiety received the highest ratings (items 86, 96, 111 and 132 in Table III). This may have partly increased anxiety during the experience, reaching a high value at the end of the experience compared to the beginning (Figure 4). Note that at the end, anxiety was the negative emotion that was experienced with the greatest intensity. Therefore, this finding constitutes an important aspect that should be taken into account in the design and construction of educational tools in order to reduce this feeling for the student.

Besides, we may observe in Figure 4 that the emotional level of embarrassment decreased throughout the experience, which probably means that the student started feeling more confident as he/she moved forward in the learning activity.

TABLE III. ANXIETY ITEMS AND THEIR RATINGS

Number item AEQ	Description	Time	$\bar{x}$
82	I get so nervous that I don't even want to start studying.	BEFORE	1,83
85	When I have to study I start to feel dizzy.		1,78
86	When I look at the books that I have yet to read, I feel distressed.		2,44
96	I worry about being able to deal with all my work.	DURING	2,44
102	While studying, I want to distract myself to reduce my anxiety.		2,94
111	When time is running out my heart begins to race.		2,83
118	I get tense and nervous while studying.		1,78
125	This subject scares me because I can't quite understand it.		1,83
132	Worrying about not completing the course makes me sweat.		2,56
141	I am concerned that I did not understand the subject correctly.	AFTER	3,56
147	When I can't keep up with my studies, it scares me.		3,17

D. *Negative deactivation emotions*

The results show that the hopelessness of students decreased while the experience with the AR tool was carried out. However, it increased again to the levels of the beginning when the task was finished (Figure 5). The authors cannot explain well the reason for this effect, although they believe that it could be related to the fact that the use of the AR tool gave them hope of learning while they were using it.

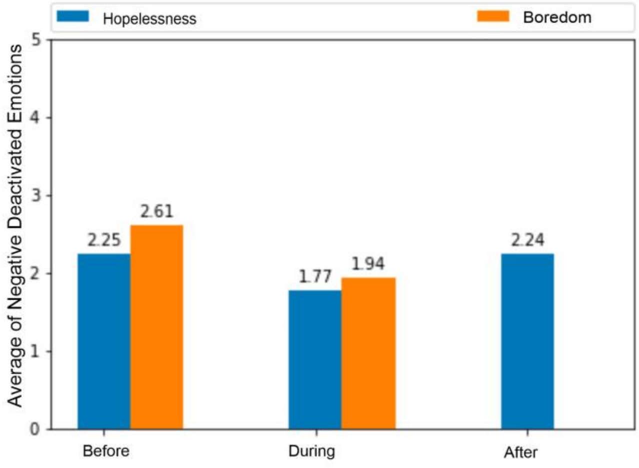

Fig. 5. Negative deactivated emotions

Regarding boredom, it was detected that it decreased while using the tool (Figure 5). This is an important aspect since boredom leads to reduced intrinsic motivation and cognitive withdrawal from the task [27]. The authors think that the use of augmented reality could have awaken the level of attention and interest of the student and therefore could have reduced boredom, perhaps increasing student's motivation.

E. Comparison of positive and negative emotions

Figure 6 shows the emotional levels grouped by positive activation (enjoyment, hope and pride), negative activation (anger, anxiety and embarrassment) and negative deactivation emotions (hopelessness and boredom). It should be noted that the positive activated emotions experienced by the students as a whole are almost twice as intense as the negative ones. The authors wonder if it could be that the use of AR in learning algorithms has something to do with this fact of experiencing positive emotions more intensely than negative ones. Which raises an interesting line of future research. Regarding negative emotions (both activation and deactivation), it could be seen that they decreased slightly while students were using the tool in the task (Figure 6, "During" section of the diagram). However, at the end all these emotions increased.

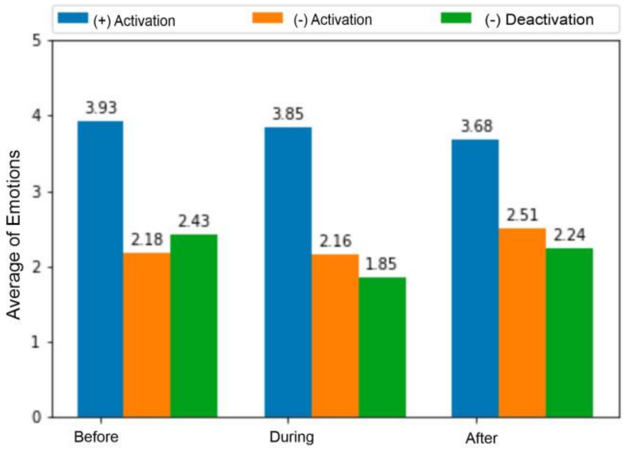

Fig. 6. General average of emotions according to time

The decrease in these negative emotions during the experience could be related to the use of the tool, while the increase detected once the task was finished could be related to the fact that they had to take a knowledge assessment test at the end of the task. This could make them anxious, angry, or hopeless.

F. Students' opinion

It was observed that students preferred to work collaboratively during the task. They spontaneously came together in pairs and in some cases even in groups of three students. Some of the students pointed out the lack of any collaborative interaction support in the tool. On the other hand, one of the problems that was observed is that some students did not have a smartphone with minimal characteristics and this caused that the camera focus was not optimal, causing the student to be bringing the mobile closer to the paper several times until the tool detected the source code. The students commented that they were surprised to learn a new subject matter through the tool and even more so because some did not know the augmented reality technology and it caused them great interest and curiosity, since they had not commonly used it in the classroom. In general, they indicated that they were satisfied with the tool and that it had been useful in the experience.

V. CONCLUSIONS AND FUTURE WORK

This article has presented a classroom experience to learn greedy algorithms using an augmented reality tool called RA-AVD. In this experience, both the emotions and feelings of the students and the level of knowledge acquired have been evaluated. The knowledge evaluation was satisfactory. The students managed to obtain an average of almost 7 (6.95) out of 10, which means that most of the students managed to understand the operation and behavior of the algorithm under study (Dijkstra's algorithm). Note that the students had no previous knowledge nor contact with greedy algorithms, thus the learning curve was high.

In relation to emotions experienced by using the tool, the experience revealed that the students experienced positive emotions (enjoyment, hope and pride) much more intensely than negative ones (such as anxiety or anger), being almost twice as intense. In addition, boredom and embarrassment decreased notably during the use of the tool, keeping the feeling of enjoyment roughly constant during its use. However, the student's level of anxiety increased from the beginning while using the tool, being almost the double at the end of the experience. This last aspect is especially relevant and it should be taken into account in the design and construction of future educational tools.

As future projects, we plan to analyze in greater depth the results obtained by carrying out a correlation analysis between emotions and learning. Furthermore, we intend to replicate the experience with a control group and compare traditional learning with the use of augmented reality.

ACKNOWLEDGEMENTS

This work has been supported by research grants iProg (ref. TIN2015-66731-C2-1-R) and e-Madrid-CM (ref. P2018/TCS-4307) with FSE and FEDER funds. The support of the GIIAR group of the Salesian Polytechnic University is appreciated.

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