A Framework for Co-Creation in Generic Educational Activities Using Swarming

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Abstract. The flipped classroom model has become increasingly popular in recent years as it supports students' collaboration leading to co-creation of knowledge. Swarming is a nature-based collaborative solution for complex problems, wherein actors' "collective intelligence" emerges significantly more advanced than the sum of its units. The knapsack problem attempts to select the subset of items with maximum desirability while satisfying a constraint on the selected items. Educationally, the knapsack problem may be mapped as the selection of a subset of literature from a large corpus that is most relevant to a research query, while maintaining some constraint such as time availability, content complexity, etc. In this work we propose a framework that models a generic educational task and maps it to the Knapsack problem to be solved using the Ant Colony Optimisation (ACO) swarming algorithm to take advantage of the co-creational characteristics of the flipped classroom paradigm. Experimentation with alternative solutions to the Knapsack problem indicate their inappropriateness to the requirements of the proposed framework, while experimentation with ACO's key parameters indicates ACO's suitability to the proposed framework.

Keywords: Educational framework · Co-creation · Swarming · Ant Colony Optimisation · Knapsack problem.

1 Introduction

In the 21st century, emerging technologies are changing the way we learn [2]. As education continues to evolve into a self-organizing vision, technology continually plays a more significant part in how education is delivered and how is used to provide support for learners' and teachers' processes [12].

The flipped classroom model's popularity has increased in recent years. It's based on the idea that students learn better when actively engaged in the learning process, rather than passively receiving information [25]. Attempting to enhance students' engagement and promote learning in classroom, educators are adopting practices promoting students' autonomy, collaboration, and teamwork [9].

Although the breadth of educational challenges students need to tackle can be significantly broad, a closer inspection identifies amongst these a small number of generic tasks that are common to a plethora of settings, such as the identification of appropriate educational resources to study. In this work, we focus on this generic task and attempt to model it as a combinatorial optimisation and more specifically, the Knapsack problem [24], that is to select a subset of literature from a large corpus that is most relevant to a specific research question, while maintaining some constraint such as time availability, content complexity, etc.

In this context, swarming methodologies, describing a group of learners working together in a self-organised and decentralised fashion without necessary the presence of a leader / organiser [3], have been shown to be highly effective. Swarming is a nature-based solution that features collaboration and decision-making demonstrated by swarms of animals exhibiting "collective intelligence" or "swarm intelligence" and decision-making in the context of simple rules and local interactions among the animals [15]. One such approach is the Ant Colony Optimisation (ACO) [22], a discrete optimisation approach based on ants' ability to collaborate aiming at the identification of the shortest paths to targets.

1.1 Motivation & Contribution

Despite the obvious complementarity of the key theme of the work, educational task modeling to combinatorial optimisation solved by swarming methods, to the best of our knowledge, existing bibliography is scarce on this amalgamation. The prevailing of the new paradigm of the flipped classroom model, despite its popularity, still requires further exploration. In addition, the collaboration aspect of the flipped classroom model is addressing the ability and use of the capability to create and co-create that still require both further examination. In order to address these challenges, this work proposes a framework that models a generic educational task of finding a subset of literary works, that best meets the task's requirements, in a large corpus, for some constraint, and maps it to the Knapsack problem that is subsequently solved using the ACO swarming algorithm. The key contributions of this work can be summarised as follows:

- modelling of a generic part of numerous educational activities into a combinatorial optimisation,
- proposing a framework that amalgamates the aforementioned modeled educational activity with a collaborative solution based on the swarming methodologies wherein the mapping of the characteristics of the three pillars of the framework are defined,
- experimentation to test the unsuitability of non-swarming solutions to the proposed framework, and
- experimentation to show the suitability of the ACO swarming solution to the proposed framework's theme.

2 Background and related work

2.1 Education

In the field of Artificial Intelligence (AI), swarm intelligence has become a critical development direction as an emerging research area that has the potential to revolutionise the way education and learning are being delivered [32].

Wong & Looi [31] introduce the concept of swarm intelligence, for developing adaptive learning systems that can adjust the difficulty of learning materials in accordance with the performance of students. Kurilovas et al. [16] propose an improved swarm-based approach to recommend appropriate learning scenarios based on learners' preferences. [21] argues the limitations of traditional methods of curriculum sequencing that can be overcome by using swarm intelligence.

Swarm intelligence algorithms are increasingly used in research, especially in personalised learning and adaptive assessment. While their use in education is still in early stages, these approaches have shown promising results in improving students' learning outcomes and providing personalised learning experiences.

2.2 Co-creativity

Co-creativity is a concept that has been explored by several researchers in different fields, from education to design, and from arts to technology. At its core, co-creativity refers to collaborative and participatory practices that involve individuals working together to create something new and innovative [18,23].

Early accounts of exploring co-creativity in the context of education [7] addressed the implications of studying collaborative creativity for education and identified the importance of fostering a supportive environment for creativity to thrive. Co-creativity in education is the key theme in [29] where the potential of co-creativity in playful classroom activities is explored. [4] investigated the effectiveness of Collaborative Creativity Learning models in developing scientific creativity skills among secondary school students. In [27], authors explored enhancing skills with augmented reality is emphasising the importance of co-creativity in technology-mediated learning environments.

These examples highlight the versatility and potential of co-creativity as a concept that can be applied across various fields and contexts. Whether in education, design, technology, or the arts, co-creativity can promote, and is ultimately based on, collaboration, participation, and innovation, making it a valuable tool for promoting creative and effective solutions to complex problems.

2.3 Inverted Classroom: A Form of Co-creation

The flipped classroom model is considered a form of co-creation as it involves a collaborative approach to learning between teachers and students. Students receive instructional material to review outside of class allowing them to take ownership of their learning and actively participate in the learning process [1].

During interactive and collaborative activities in the flipped classroom, students can work together to co-create knowledge by sharing their ideas, insights, and perspectives [13]. Teachers can act as facilitators, guiding and supporting students as they work together to make sense of complex concepts and ideas. This collaborative approach to learning can lead to improved learning outcomes for students [14].

In addition to fostering collaboration between students, the flipped classroom model can also encourage co-creation between teachers and students [20]. Teachers can create instructional materials that are more tailored to the needs and interests of their students, while students can provide feedback and contribute their own ideas and insights to the learning process [30].

2.4 Swarming & Ant Colony Optimisation

To develop effective solutions to complex problems, nature-based solutions, such as the principles of "swarm intelligence" are of importance. Swarm intelligence is traced back to the biological study of how insects interact with each other in a self-organised manner [10]. According to Bonabeau et al. [6], social insects, use swarm behavior to coordinate activities that are otherwise too complex for each unit to accomplish. Combining swarm intelligence & algorithmic optimisation techniques has been shown effective in solving complex problems [22].

ACO [22] is a discrete optimisation approach based on the ability of ants to collaborate to identify the shortest paths to targets. The concept behind ACO is the use of artificial ants traversing paths on a graph with nodes being the components of the solution to a challenge. As part of the ACO approach, simulated chemical pheromones are used to attract ants onto better trails. Ants, collaborating, explore randomly and monitor chemicals left by other ants.

2.5 Knapsack Problem

As its name implies, it arises from the problem of filling a fixed-sized knapsack with the most valuable items. The knapsack problem, as defined by Martello and Toth [24], is: "*We are given a set of n items, each item i having an integer profit z_i and an integer weight w_i. The problem is to choose a subset of the items such that their overall profit is maximised, while the overall weight does not exceed a given capacity C.*"

This can be expressed, as per [24], using Equations $max \sum_{i=1}^{n} z_i x_i$ and $\sum_{i=1}^{n} w_i x_i \leq C$ where C is the total knapsack load capacity; z_i is the profit on an object i; w_i is the weight of an object i; C,z_i, and w_i are all integers and positive numbers; and $x_i = 0$ when an object i has not been loaded into a knapsack or $x_i = 1$ when an object i has been loaded into a knapsack.

In this paper, we are focusing on the most commonly used case, the "0-1 knapsack problem", which restricts the number of copies of each item to zero or one. This variation is better suited for our scenario whereby students pick academic papers only once in order to complete a specific task. There are numerous solutions for the knapsack problem [19], ranging from examining all combinations of items, to dynamic programming algorithms to swarming algorithms.

The "Brute-force" Solution In order to address the requirements of the 0-1 knapsack problem one might resort to a methodology that evaluates all alternative potential solutions and then keep (one of) the best. This approach requires the non-repeating combination of sampling r of n discrete elements as per Equation $C(n,r) = \frac{n!}{r! * (n-r)!}$.

Moreover, given the requirements of the Knapsack problem to allow one or more elements to be selected, the combinations of all scenarios $\forall r \in [1, n]$ must be considered leading thus to the evaluation of the number of combinations using Equation $\|\mathbf{combinations}\| = \sum_{r=1}^{n} C(n,r)$.

As this method does not utilise any optimisation, the number of combinations it has to examine, even for relatively low numbers of the N elements is significantly high. The number of combinations for one or multiple agents (examining entities of the elements to be included in the knapsack, in a form of parallelisation of the task) when the number of distinct elements and the number of samples are equal for values ranging from 1 to 40, is leading to maximum numbers of combinations reaching values near 10^{12}. As far as the form of parallelisation in the examination processes with multiple agents, the number of concurrent examining agents does indeed significantly effect the number of combinations per agent but given the relative high number of combinations to be examined altogether (and the equal distribution of examinations between them), the combinations per agent still remain quite large.

Accordingly, the "brute-force" solution to the Knapsack problem, despite the fact that it always reaches the best solution(s), becomes prohibitive costly for relatively low numbers of discrete elements in terms of the sheer number of combinations that must be evaluated.

Dynamic Programming Solution Another way to solve the 0-1 Knapsack problem, is using the Dynamic Programming (DNP) algorithm which works on the principle of using a table to store the answers to solved sub-problems. Whenever a sub-problem is surfaced again, the answer can be looked up in the table rather than having to be computed again. As a result, dynamic programming-designed algorithms are incredibly efficient.

Unfortunately, as per the theme of this work, it cannot be applied on our educational model, i.e. map it to students co-creating solutions by accessing informative resources / papers. Nevertheless, it is used herein as a point of reference to obtain exact solutions, so we can compare the results to other algorithms for the solutions for the knapsack problem, such as the ACOK algorithm, discussed in the sequel (Section 2.5).

ACO Algorithm Solution In this work, to solve the 0-1 knapsack problem, we will employ the ACO algorithm and compare it against the brute force method, as described in Section 2.5. Due to the long time the brute force algorithm takes and the fact that the ACO algorithm does not guarantee always a 100% optimal [11] solution, we will be using the aforementioned dynamic programming algorithm, as described in Section 2.5, to obtain the exact solution so we have a fixed target to compare against it.

Thus, we utilise a ported version of the standard ACO algorithm tailored for the 0-1 knapsack problem 2.5 (ACOK).

An artificial ant's probabilistic solution building process is biased by pheromones and heuristic variables (α, β) in ACO. The ants' movements are determined by stochastic local decision policies based on two composite parameters, namely, the pheromones and the attractiveness of the path leading to an, also, attractive edge [33]. Each ant incrementally constructs a solution to the problem by moving iteratively in various directions. In the process of completing a solution, the ant changes the pheromone value on the visited items, aiming at pheromone information guiding future ants.

In more detail, each ant moves from one state i to another state j according to a transition probability rule p_j [28], as shown in Equations $p = \frac{\tau_j^\alpha \mu_j^\beta}{\sum_{j \in N_i} \tau_j^\alpha \mu_j^\beta}, \ for\ j \in N_i$ and $p = 0, for\ j \notin N_i$.

The α parameter is responsible for controlling the impact of the pheromone trail τ_j, which is the collective memory of the colony. By increasing the value of α, ants are more likely to follow pheromone trails that other ants have previously followed. Parameter β controls the impact of the heuristic information (attractiveness μ_j), which is local information available to the ants regarding the problem. By increasing β, the ants are more likely to choose paths that appear to be more promising based on the specific characteristics of the problem. The neighbourhood N_i of state i is composed of items that can be used as part of the construction of a partial solution. The attractiveness μ_j refers to the problem-specific heuristic information that is used by the ants to evaluate the desirability of an item from the neighbourhood N_i being added to the N_i solution under construction. z_j is the profit and w_j is the weight of the selected item j. Thus, attractiveness [28] can be expressed as per Equation $\mu = \frac{z_i}{w_j^2}$.

When a solution has been found, each ant deposits an amount Δ_τ of pheromone τ on all the items included in the solution following the pattern using of Equation $\tau = \tau + \Delta\tau$. The amount Δ_τ of pheromone deposited on each item is proportional to the quality of the solution that the ant has found [28]. This is expressed as shown in Equation $\Delta\tau = f(Q) = \frac{1}{1+\frac{z_{best}-z}{z_{best}}}$.

Finally, a mechanism of evaporation, as far as pheromones are concerned, is incorporated into the process of ACO and respective implementation of algorithms in order to avoid fast convergence to a sub-optimal solution [28]. The strength of evaporation is controlled by the parameter ϱ which represents the evaporation rate. The evaporation is calculated using Equation $\tau = \varrho\tau, \varrho \in (0, 1)$.

3 Proposed method

This paper introduces and examines a framework for educational scenarios where a teacher/enabler maps an educational task to a distributed and decentralised process during which students cooperate to solve a challenge or, more generally, perform an educational task. As a result, students themselves co-create the solution, thus the solution they develop is a result of their collective output.

In swarm learning, the teacher/enabler plays a different role compared to traditional teaching approaches [17]. The teacher is not necessarily an instructor, but rather more of a facilitator whose primary responsibility is to support and guide students as they work collaboratively in order to learn. The teacher/enabler should first identify the educational task or goal that they want to achieve through their teaching. This could involve defining the learning objectives, outcomes, and/or competencies that they want their students to develop. In examining the integral part of education, i.e. the students, and more specifically a class of students seeking out new knowledge, we observe that it is directly related to the ant colony paradigm and that makes ACO an ideal candidate for a swarming approach for the aforementioned task.

One of the key initial activities of students is identifying information relating to the educational task. To achieve this goal, students are expected to examine sources (proposed by the teacher/enabler or according to will) to gather as much information about the subject in question. Each source is evaluated both by students and peers of its authors. The relative quality of a source depends on how well it meets the student's informational needs. Additionally, students' evaluation of a source requires a thorough examination of the source's content, including its bibliography thus affecting the whole examination process by adding more resources. Moreover, by citing a source within their own work, peers of a source's authors, in addition to providing references where due, they indirectly provide a measurement of evaluation, similarly to PageRank for web-pages [5].

The process of selecting papers that contribute most to the task at hand represents a well-defined problem domain as already discussed in Section 2.5, the Knapsack problem that dates back to the early works of the mathematician Tobias Dantzig [8]. To address the mapped educational challenge with the Knapsack problem using the aforementioned swarming solutions, the ACO approach, being a generic approach rather than a specific algorithm, it needs to be tailored to the particular problem under consideration i.e. education. To achieve that we use the Knapsack problem as an intermediary.

As described in Section 2.5, the knapsack problem attempts to select the subset of items with maximum desirability while satisfying a constraint of the total weight of the items [26]. Within the context of learning, the knapsack problem can be applied to the selection of resources that address the educational challenge, i.e. to select a subset of resources from a large corpus that is relevant to a specific research question or topic, based on factors such as time availability, reading capacity, and content complexity. For example, given a set of papers with associated relevance scores, citation counts, and a limited amount of time a student has to devote to reading, a student will have to determine the subset of papers that maximises the overall relevance or information gained based on the time limit and reading capacity constraints.

Accordingly, the proposed framework utilises the notions of (a) the Knapsack problem as a generic methodology to identify the best subset of resources that maximise their value while adhering to a (weight) constraint, (b) the ACO swarming algorithm that is inspired from ants for the task of identifying the aforementioned subset, and (c) the educational domain wherein one of the common processes includes the examination of educational resources in order to address an educational need. The fusion of these notions is based on a mapping between their key characteristics, as described in the sequel.

For the pillars educational process and Knapsack problem: educational sources are mapped to items; the number of bibliographic entries within each source are mapped to the item weight; citations received by a source as well as the source's ability to address the informational need are mapped to the desirability of each item; and, the combinations of subset of resources that must be examined to address the educational need are mapped to iterations.

For the pillars Knapsack problem and its ACO swarming approach: items are mapped to locations and/or processes that meet ants' need (e.g. foraging); item weight is mapped to the process of ACO that introduces realism by including constraints; item value is mapped to the desirability of a path; and, iterations are mapped to the paths travelled by ants to meet their need.

For the pillars ACO swarming approach and educational setting: parameter Alpha (α) is mapped to the impact of collective memory on students' decisions; parameter Beta (β) is mapped to the impact of local student information; evaporation rate is mapped to the capability of students to retain a varying persistence collective memory; iterations are mapped to the combinations of subset of resources that must be examined to address the educational need; ants are mapped to students; ants' need is mapped to the educational need / process; and, places that ants meed their need is mapped to the educational resources.

4 Experimental evaluation

4.1 Experimental Setup

A simulation model was developed in order to test various scenarios using the ACOK algorithm, as well as to run sensitivity tests for the ACOK input parameters to determine their effectiveness. The simulation model was implemented in the .NET framework using C#. The machine characteristics that we run the tests are, Intel Quad Core i7-6820HK CPU @ 2.70GHz with 16 GB RAM.

In order to have a simulation model that is as realistic as possible, the experiments were conducted using graphs directly obtained from Connected Papers via their REST API. Through Connected Papers, researchers are able to locate relevant academic papers based on the field of study in which they are interested. For the purposes of this work, the graphs experimented on where based on papers that research ICT methodologies for the reduction of risks and vulnerabilities closely related to climate change (e.g. flood risk, risk of fire, erosion, landslides and landslides). This selection was made as a preparation for future application of the proposed framework in various levels of educational institutions in order to promote / educate on issues of the climate crisis.

We tested using a set of three graphs with 20, 30 and 40 papers respectively. For each graph, we run a test scenario with the ACOK algorithm parameters set as follows. Number of Iterations: 5, 10, 100, 1000; Number of Ants: 1, 2, 4, 6, 8, 10, 15, 20, 25, 30, 50, 100; Evaporation Rate: 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1; Alpha: 0, 1, 2, 3, 4, 5; and, Beta: 0, 1, 2, 3, 4, 5.

Default parameter values We initially performed a short sensitivity analysis for parameters Alpha (α), Beta (β), and Evaporation Rate (ϱ) that lead to the best performing values of these parameters. Given these results, we selected as the default values for Alpha, Beta and Evaporation Rate to be 1, 2, and 0.8 respectively. In our experimentation process, the Number of Ants never exceeds the value of thirty which maps favourably to the paper's theme of typical number of students in a class. Also, the maximum Number of Iterations to be executed, within which the solution is to be found, is selected to be 10 as, per our theme, most repetitive tasks bigger than these are deemed to become exhausting and boring for the students participating in the experiments.

4.2 Evaluation Results

We performed two experiments: (i) Measure success rate for varying number of ants involved, and (ii) Measure the number of iterations at which the optimal solution found for varying number of items in the graph.

All scenarios have been executed 10 times for each variation of the parameters in order to average out the stochasticity of the heuristic process of the algorithm. The parameters' value ranges used for the ACOK, leading to a resulting dataset of 18,000 entries, are: Alpha: 1; Beta: 2; Evaporation Rate: 0.8; Number of Iterations: 1…10, Number of Ants: 1…30; and, Items in graph:20, 30, 40.

Average Success Rate per Ant This experiment involves testing the impact of the number of ants involved on the success rate. That is, the ACOK's average success rate against the exact solution produced by the DNP algorithm, as described in Section 2.5. Thus, we measure this as a percentage of the output produced by ACOK against DNP since, as already mentioned, ACO does not always guarantee the exact solution [11] hence the use of DNP.

Thus, the first experiment tests the impact of the number of ants involved in order to find the exact solution. Accordingly, we measure the average percentage of the success rate against DNP's performance.

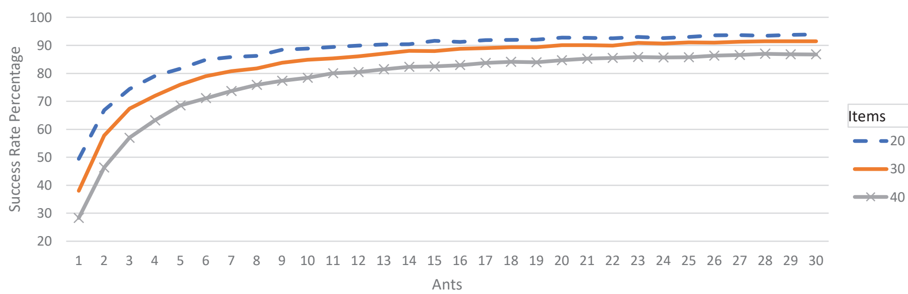

Fig. 1: Average Success Rate per Ant

Examining the results received shown in Figure 1, we observe that for all three cases and for one ant, all three alternatives of the graph size present the worse success rate of their respective examination. The results increase in an exponential manner as more ants are incorporated into the experiment, reaching at around 90% in average for 30 deployed ants. The result's explanation presents as straightforward since the introduction of more ants allows more combinations to be processed within a set number of iterations hence the possibility to find the best solution with higher success rate is also increased. Moreover, we observe that for smaller search spaces, i.e. having less items to process, the success rate is higher than for larger search spaces (i.e. graphs with 20 items as opposed to graphs with 40 items).

Average number of iterations the best result found at The next experiment concentrates on how the number of ants and number of items in a graph affect the number of iterations needed in order to reach to the optimal solution. Thus, in this experiment we examine the average number of iterations that the optimal solution is found at for varying numbers of ants.

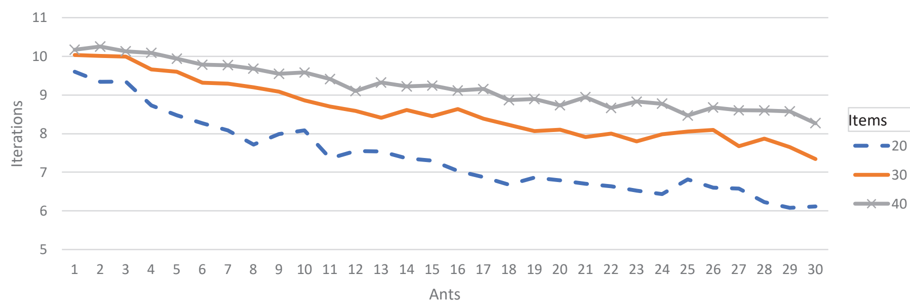

Fig. 2: Average number of iterations the best result found at.

From the results received in this experiment, as shown in Figure 2, we observe that the maximum number of iterations at which we find the most optimal solution, peaks at around 10 iterations (averaged values). We also observe that as more ants are added to the colony, up to a total of 30, iterations are almost consistently decreasing with the minimum value reaching 6 iterations.

It follows then that as more workers (ants) are being added, the parallelism of the process is increased and thus fewer iterations are required, as expected. Moreover, we observe that the size of the graph, representing the search space, affects proportionately the iteration at which the identification of the most optimal solution is made at, for a given size of workers, again as expected.

5 Conclusions

The meteoric popularity of the flipped classroom model in recent years has been based on its ability to enhance students' engagement and promote learning through students' collaboration in order to address a complex educational task, thus leading to the co-creation of knowledge. Such co-creation of knowledge is also observed in nature-based collaborative solutions, among others, in the form of swarming for efficient and effective tackling of complex problems.

One of the key aspects of the flipped classroom model is the shift of class' time activities to non-class time activities. Students initiate tasks like examining the bibliography outside the classroom thus prompting the generic educational task of the selecting the best subset of educational resources that best addresses a complex educational challenge given constraints, a task efficiently addressed by the Knapsack problem.

Building on the aforementioned aspects of an educational task modeled to combinatorial optimisation solved by swarming methods, in this work we propose a framework that models the generic educational task of identifying a subset of literary works, that best meets the task's requirements, from a large corpus, for some constraint, and maps it to the Knapsack problem that is subsequently solved using the ACO swarming algorithm.

Experimentation with alternative solutions to the Knapsack problem, such as "brute-force" and dynamic programming, indicate their inappropriateness to the requirements of the proposed framework, while experimentation with ACO's sensitivity and key parameters indicate the effectiveness and efficiency of ACO to the proposed framework.

Future plans include the mapping of more generic and specific educational activities to the proposed framework. Moreover, future update of this work includes experimentation with more swarming approaches in order to test their effectiveness and efficiency. Finally, future plans include the application of the proposed framework in various levels of educational institutions in order to promote / educate on issues of the climate crisis.

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