Pedagogical Agents for Scientific Crowdsourcing

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Abstract. Scientific crowdsourcing, or "Citizen Science", is a form of research collaboration involving members of the public in scientific research projects to address real-world problems. Frequently organized as a virtual collaboration, these projects are a type of open movement, with collective goals addressed through open participation in research tasks. Over the past decade, researchers and practitioners in the field of scientific crowdsourcing have presented tools, methods, and techniques for answering research questions that predominantly center around leveraging the help of volunteers only to perform tasks of low complexity (*i.e.*, identifying objects in images) due to the difficulty and skepticism involved in delegating both larger and more critical portions of the scientific research process to every-day citizens. In this paper, we present a set of pedagogical agents designed to guide citizen scientists in understanding the lifecycle of the research question (*i.e.*, the question being answered through crowdsourcing) while simultaneously learning how the crowdsourced task should be correctly performed. This paper concludes with a discussion on both potential methods of evaluation for the set of pedagogical agents and a direction for future work.

Keywords: intelligent tutoring system, citizen science, crowdsourcing, training.

1 Introduction

Over the past decade, crowdsourcing has become a pervasive utility for completing tasks that cannot be automatically and independently completed by machines. Commercial crowdsourcing (*e.g.*, Amazon Mechanical Turk[1]) has become a viable and popular outlet that allows large numbers of online workers to earn compensation for performing micro-tasks, which are concise subsets of larger tasks that usually require little to no specialized expertise to complete. Similarly, scientific crowdsourcing, or "Citizen Science", has become a prominent approach for academic-based projects where volunteers, or 'citizen scientists', perform simple tasks (*i.e.*, identifying objects in images) on large academic datasets. Unlike commercial crowdsourcing, these projects often have a much higher or lower lifetime as they offer a unique opportunity for every-day citizens to contribute to

[1] http://www.mturk.com/

new discoveries in the sciences and humanities. In both practice and the literature, the public is engaged in online and offline (*i.e.*, field work) citizen science, and within this paper, we explicitly target *web-based* citizen science, such as GalaxyZoo [20], where large numbers of citizens participate in science through the Internet. Regarded as one of the most successful citizen science projects, GalaxyZoo, hosted on the Zooniverse [28] crowdsourcing platform, launched in 2006 and asks volunteers to help identify galaxies in images collected from the Sloan Digital Sky Survey dataset. Over the course of the project's existence, volunteers have collectively made sizable contributions in the field of physics and astronomy, unknowingly identifying previously unknown galaxies, such as the Green Pea galaxies [5]. The phenomenon of volunteer-driven discovery is not limited to GalaxyZoo as discovery in other citizen science projects (*e.g.*, Planet Hunters [12], Disk Detective [18], Ancient Lives [33]) have also been fueled by volunteers.

In most citizen science efforts, volunteer participation takes place in a basic, repetitive manner (see Figure 1). For example, GalaxyZoo operates at the second level of participation for citizen science as it asks volunteers to offer their interpretation of what is and is not a galaxy within a particular image. In addition, a project that operates at the first level of participation would center around a highly objective task or question (*e.g.*, Is Barack Obama the President of the United States of America?). To our knowledge, the third and fourth levels of participation have been explored only in the context of field-based citizen science, specifically within the space of ecology and conservation [31]. However, outside these areas of scientific and academic research, instances of both levels of participation are few and far between. The literature on public participation in science tells us that many scientists simply dislike "engaging with the social and public side of science at a deep level", which is necessary for the the latter levels of participation in citizen science [34, 30]. The lack of interaction between scientists and the public prevents the latter from understanding both the value of their contributions and what a career in science entails.

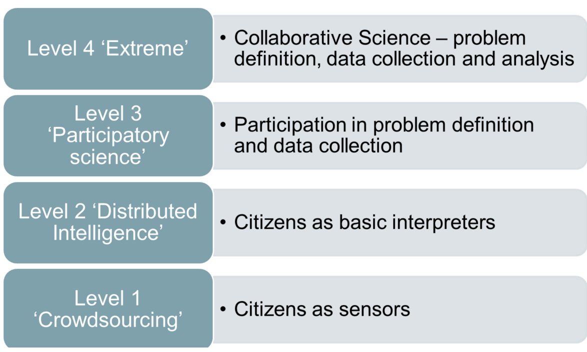

Fig. 1: Hierarchy of participation in citizen science projects.

One possible explanation for the lack of "extreme citizen science" and "participatory science" efforts is scientists' skepticism of crowdsourcing as a method for collecting high-quality data as most scientific tasks require domain-specific knowledge in order to perform correctly. A number of recent studies have collectively expressed both doubts in data quality and the inability of volunteers to correctly perform a scientific task as key factors that drives academic skepticism [4, 19]. In the context of both commercial and volunteer-based crowdsourcing, a variety of unique training methods have been investigated, evaluated, and put into practice. However, no proposed training method has yet to facilitate a change of attitude among scientists in moving toward higher levels of participation in citizen science projects. We acknowledge that a number of other areas of research (*e.g.*, trust modeling) are relevant to the problem of data quality, but choose to explicitly mention training as it is the only opportunity to instill excitement, among other positive emotions (*e.g.*, curiosity), into the necessary process of instruction.

In this paper, we present a set of pedagogical agents designed to guide citizen scientists in understanding the lifecycle of the research question (*i.e.*, the question being answered through crowdsourcing) while simultaneously learning how the crowdsourcing task should be correctly performed. The design of the agents is driven by the notion of guiding the citizen scientists in understanding both how the research question formed and how the research question can be answered. We specifically argue that such guidance can be used to motivate the citizen scientists to continue their participation and help members of the public understand how they can make more meaningful contributions to science in more intricate and advanced ways (*i.e.*, suggesting an alternative hypothesis or research question). We conclude with a discussion on a potential method of evaluation for the set of pedagogical agents, a brief conclusion on how the system answers the challenges currently facing elevated participation in citizen science, and a direction for future work.

2 Related Work

2.1 Intelligent Tutoring Systems

The foundation of this paper is rooted in the area of intelligent tutoring systems of which initiated from the fundamental aim "to have automated tutors emulate the personalized teaching offered by one-on-one instruction from real teachers" [6]. The definition of intelligent tutoring systems has progressively changed over time as more advanced techniques for inference have been explored, and a more modern definition for intelligent tutoring systems, aggregated from the literature and proposed by Ma and Adesope [22], is as follows:

1. Performs tutoring functions by (a) presenting information to be learned, (b) asking questions or assigning learning tasks, (c) providing feedback or hints, (d) answering questions posed by students, or (e) offering prompts to provoke cognitive, motivational or metacognitive change.

Agent	Function	Solicited
The Guide	Anticipate questions and provide answers to questions.	Yes
The Critic	Provide feedback on the current progress.	Yes
The Mentor	Provide unique feedback on the current progress occasionally.	No
The Interviewer	Ask questions learners should be asking themselves.	No
The Observer	Monitor learner progress and direct other agents. Invisible.	-

Table 1: Five functionally-unique agents presented in Joyner and Goyal [16].

2. By computing inferences from student responses constructs either a persistent multidimensional model of the student's psychological states (such as subject matter, knowledge, learning strategies, motivations, or emotions) or locates the student?s current psychological state in a multidimensional domain model.
3. Uses the student modeling functions identified in point 2 to adapt one or more of the tutoring functions identified in point 1

Within this area of research, we situate our work in the space of *Pedagogical Agents*, which Mabanza and de Wet define as "character(s) enacted by a computer that interacts with the user in a socially engaging manner" [23]. The presence of these typesof agents is broad as they can be found in a variety of disciplines, such as medicine, math, law, language learning, automotive, and armed forces, and across all age groups as well [23]. One example of a well-known pedagogical agent is Clippy[2], an animated character that was designed to assist users in earlier versions of Microsoft Office.

Joyner and Goyal The basis for the bulk of the proposed approach is Joyner and Goyal's work which studied how inquiry-driven modeling for science education could be improved through the use of intelligent tutoring agents [16]. Inquiry-driven modeling draws from inquiry-driven learning [11], a pedagogical method of instruction where learners iteratively participate in a question-answer process until arriving at a final solution, and scientific modeling, which utilizes abstractions *e.g.*, graphs, visulizations, etc.) as representations.

In their work, the author's presented a set of 5 functionally unique tutors that were designed to facilitate inquiry-driven modeling in the context of complex ecological processes (see Table 1). The authors state "each tutor plays a different functional role with regard to interaction", which indicates the opportunity for additional or fewer agents could exist given additional forms of interaction. Within this set of five agents, each agent provides feedback in the form of text and uses a unique decision-making routine to decide which feedback to provide. Although never explicitly revealed in the paper, the decision-making routines seem to be carried out using a simple rule-based reasoning system (see Figure 2).

[2] https://en.wikipedia.org/wiki/Office_Assistant

The authors evaluated the system using small teams of middle-school students in one-week Life Science summer school classes. Student teams were collectively asked to complete two projects where they leveraged inquiry-driven modeling to problem scenarios in the life sciences. Students were pooled into two conditions where students in only one condition were exposed to the intelligent tutoring agents during the first project. Both experimental conditions of students were not exposed to the intelligent tutoring agents for the second project. An analysis of the effects of interacting with the set of intelligent agents was performed on the basis of student interactions with the system (*e.g.*, frequency of creating or deleting a hypothesis), which the authors argued was representative of the students' decision-making process. The authors concluded that interacting with the intelligent tutoring agents did, in fact, improve students' ability to leverage inquiry-driven modeling in the context of science education.

2.2 Training Methods for the Crowd

There have been a number of studies that have proposed and evaluated approaches for training a crowd of participants, each of which has their own background and expertise. Oleson et al. [25] proposed the use of gold standards as a form of training on relatively simple tasks, primarily exploring how gold standards can be used for quality assurance. Willett et al. [32] , Mitra et al. [24], and Ghadiyaram et. al [13] suggested using examples for training workers and for calibrating their work to match the requesters' expectations on visualization, annotation, and labeling tasks respectively. Incorporating the notion of personalization into training, Singla et al. [29] used machine learning to optimize what training examples to show workers in simple classification tasks based on a short pre-phase test. Dow et. al [10] and Park et. al [27] explored and validated synchronous feedback as an effective method for training scenarios aimed at refining an ability through iteration and peer-review. Zhu et al. [35] conducted a study that found reviewing the work of other workers is a more effective form of training than repetitiously performing more tasks and alluded that it was also more

IF: The student has recently dismissed one of their models; AND: The student had not yet demonstrated proficiency with proposing and dismissing models according to the Observer's model of the student; AND: The student has not yet received positive feedback on dismissing models.

THEN: Make feedback available, "I see you've dismissed one of your initial hypotheses. Well done! Proposing and then ruling out hypotheses is an important part of science. It's crucial to reflect on your ideas and understand when you have disproven an earlier hypothesis."

Fig. 2: A decision-making rule for the *Mentor* agent in Joyner and Goyal [16].

effective than feedback-based approaches in general. More recently, Doroudi et. al [9] conducted a comprehensive study across the presented methods of training for crowd-workers and concluded that validating the work of others is more effective than other forms of training for complex tasks.

3 Pedagogical Agents for Scientific Crowdsourcing

3.1 Overview

In this section, we present an intelligent tutoring system that is composed of 6 unique agents, each of which have some functional responsibility with respect to facilitating the learner's education experience and their understanding and significance of the scientific question being asked. First, we introduce a new agent, the Peer agent, which is primarily designed to encourage reflective learning by asking the learner to explain their reasoning for a particular choice. Second, we introduce a more advanced model for decision-making among the agents based on the notion of Markov decision processes, a representation that uses action-based probabilities to dictate decisions [26].

System Implementation A preliminary implementation of the intelligent tutoring system was performed by creating and integrating an instructional playback module into Mozilla Labs' TogetherJS[3], a JavaScript library that facilitates real interaction between two or more people over the web (see Figure 3). The interface is shared between all participants within the learning session and shows every participant's mouse on the screen. The interface also facilitates chat between all participants.

[3] https://www.togetherjs.com

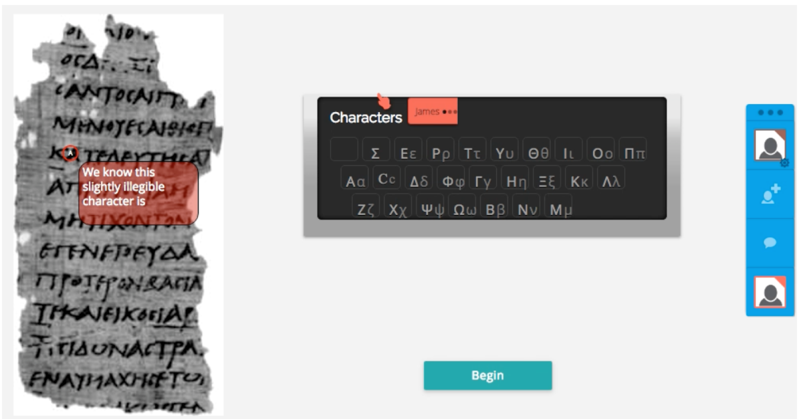

Fig. 3: A playback recording of *James*, an artificial agent, teaching a student how to transcribe papyrus using the modified implementation of TogetherJS.

Distinction from Joyner and Goyal As stated in Section 2, Joyner and Goyal's work [16] is the basis for the proposed approach. With that being said, it is important to understand the different scenarios that each work targets.

The first distinction between the two works is that Joyner and Goyal framed and investigated their proposal in the context of small teams of middle-school students solving science education projects. We certainly do not disagree that science education projects and citizen science tasks bear some level of small similarity. However, we do argue that the intended scenarios for the two systems are exceptionally different. Instead of having teams of participants, our approach operates on the basis that only a single learner (*i.e.*, citizen scientist) interacts with the agents in a given learning session. This is fundamentally different from the intended use of Joyner and Goyal's proposed system.

The second distinction between the two works is much more broad. Our work is situated in the space of crowdsourcing where the outcome of interacting with the system is much more crucial. For example, one primary goal of Joyner and Goyal's work was to facilitate scientific interest in young students. For these particular students, there are undoubtedly many more opportunities in the span of their remaining education to intervene in order to spur an interest in science. However, this is not the case for our work. In many cases, citizen scientists give a particular project a chance to satisfy their curiosity, and once they've satisfied their curiosity, they rarely return [8].

The third and final distinction between the two scenarios is the architecture of the intelligent tutoring system presented in the two works. Our work extends the system proposed by Joyner and Goyal by incorporating an entirely new agent that offers a new interaction previously unsupported in their work. In addition, we propose a fundamentally different method of representation and reasoning. Each of these differences are discussed in detail below.

3.2 The Peer Agent

Here, we introduce the Peer agent – an agent that emulates the role of a learning companion that has the following functional responsibilities in the system:

1. Encourage reflective learning by asking the learner to explain their reasoning for a particular choice.
2. Share the responsibility of learning by visibly receiving instruction from the other pedagogical agents.

The decision to introduce a Peer agent (in addition to each of the agents listed in Table 1) is supported by the many bodies of literature that study how learning is affected by the presence or interaction of peers. The functional responsibility of the Peer agent was also dictated by these works as well. Okita and Schwartz presented a study that concluded it was more beneficial to allow students to watch an instructional agent teach a peer agent than to require students to learn independently, and Matsuda et. al concluded that asking students to teach other students by explaining an answer was effective for their proposed intelligent tutoring system. Both of these studies are inline with what the crowdsourcing literature has found in allowing crowd-workers reviewing and watching the work of other crowd-workers as an effective form of training [35, 9]. The notion of peer-based tutoring is also a topic supported by a large body of literature [7, 6].

3.3 Representation and Reasoning for Agent Decision-Making

Partially-Observable Markov Decision Processes Although the majority of the agents in our proposed system have identical names and responsibilities from those presented in Joyner and Goyal [16], the decision-making module for each of the proposed pedagogical agents is fueled through very different means. The reasoning and representation of the proposed agents is powered by partially-observable Markov decision processes (POMDPs) [21].

It is important to first explain Markov decision processes (MDPs), which are foundational to POMDPs. Bearing some similarity to finite state machines, MDPs are structures for modeling states and the transitions between them. MDPs consist of: a finite set S of states; a finite set A of actions; a stochastic transition model $\Pr: S \times A = \Delta(S)$,with $\Pr(t|s, a)$ denoting the probability of moving from state s to t when action a is taken, and $\Delta(S)$ is a distribution over S; and a reward assigning $R(s, a, t)$ to state transition s to t induced by action a (see Figure 4). The goal of any MDP is to compute an optimal *policy* that satisfies immediate rewards and future gains for our agent. In the case of our agents, rewards and future gains are characterized by the learner, or citizen scientist, learning to better perform the scientific task, which can be exhibited in a number of ways (*e.g.*, correctly answering a question from the Interviewer agent).

Despite being useful for probabilistically modeling for reward and future gain, MDPs are limited by their assumption that the entire space in which an agent is operating is fully observable. We have chosen to leverage POMDPs for the decision-making module in each of our agents (*i.e.*, there exists a PODMP for each agent). Because states cannot be observed directly, POMDPs extend the MDP model and consist of: a finite observation set O and a stochastic observation model with $Pr(o|s)$ denoting the probability of making observation o while the system is in state s. The goal of the stochastic observation model is to relate observable signals to the underlying state. As the state of the system state is not

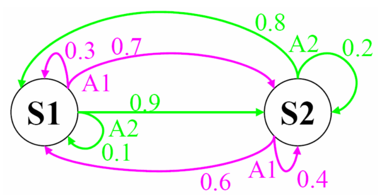

Fig. 4: A Markov decision process that models two different states.

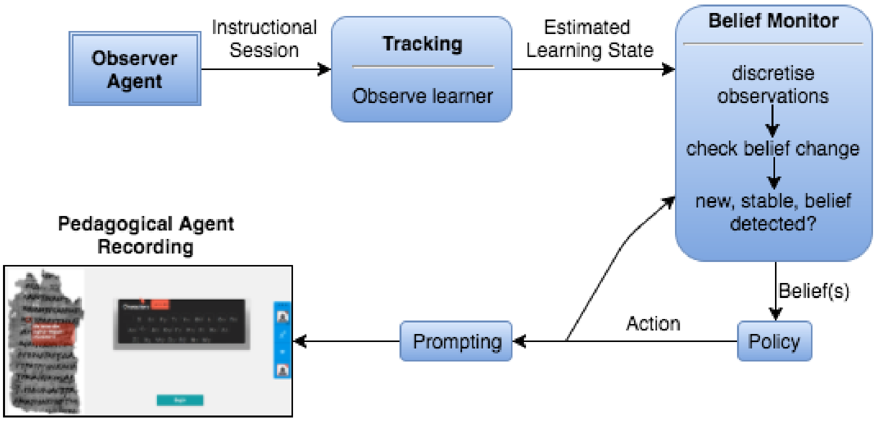

Fig. 5: A schematic of the proposed system demonstrating how (1) the observer observes and estimates learning state, (2) a belief monitor that estimates the progress of the learner, (3) a policy maps the belief state to a particular action for an agent, and (4) a mechanism for carrying out prompts to the agents. The system action is fed back to the belief monitor to enable sequential updates of the belief state, if necessary.

known with certainty, the computed policy maps belief states (*i.e.*, distributions over S) into choices of actions.

To more clearly convey how the POMDP is utilized, we have included a high-level schematic of the proposed system, inspired by [14], that demonstrates the relationship between the Observer agent and each of the other pedagogical agents (see Figure 5). The Observer agent monitors the instructional session, tracking the progress of the learner. At some pre-determined interval, the Observer measures the learner's estimated learning state and sends it to the belief monitor, which estimates the learner's progress toward correctly performing the task. A policy is computed and the recommended action is taken by a pedagogical agent.

4 Proposed Evaluation

4.1 Research Questions

In the context of the proposed system, there are many new and exciting research questions. For example, one such question is how agent personas may affect the learning experience of the citizen scientist. This particular question has been investigated in the space of now dated pedagogical agents [3, 2] and would be interesting to answer within the context of the proposed system. One other unique research question centers around the notion of "learner interuptability" and when might be the most optimal time for a particular agent (*i.e.*, the Interviewer or Mentor) to intervene in order to provide feedback or potentially do something else entirely (*i.e.*, keep the citizen scientist engaged). This particular research question exhibits relevance to earlier work in the area of mixed-initiative interaction where "optimal intervention" was a key topic of concern [1, 15].

While each of these questions are undoubtedly interesting and offer new insight into their respective areas of interest, we argue that any formal evaluation should first and foremost answer the following research questions:

RQ1: Does interacting with the set of pedagogical agents improve citizen scientists' ability to correctly perform a scientific crowdsourcing task?

RQ2: Does interacting with the set of pedagogical agents allow and encourage citizen scientists' to participate at a higher-level (*i.e.*, "participatory science" or "extreme citizen science")?

These research questions were collectively chosen as they explicitly ask about the pedagogical agents' ability to address the challenges posed in the space of citizen science that were heavily discussed in the earlier portion of this paper.

4.2 Study Design

Although no 'real' experiment is presented in this paper, it should be noted that the proposed research questions and the following proposed experiment are representative of how a 'real' study of interaction would be conducted in practice. In fact, the following proposed experimental design closely mimics that of Joyner and Goyal's experiment that was conducted using small teams of middle-school students [16].

Experimental Design To determine the effectiveness of interacting with the set of pedagogical agents, we would conduct an online experiment using Curio[4], a platform that hosts scientific crowdsourcing projects in collaboration with scientists across the world. For a particular scientific crowdsourcing task, we would recruit approximately 200 citizen scientists for two different citizen science projects. Citizen scientists would be pooled into two conditions where only one condition received access to the pedagogical agents for the first citizen science project. For the second citizen science project, neither experimental condition would have access to the pedagogical agents. This style of experimental design is popular in medical science (*i.e.*, for assessing the quality of medical treatments). Participants would also be asked to complete pre- and post-questionnaires that contained questions designed to extract information about intrinsic motivation in science to better understand how exposure to pedagogical agents affected volunteer perceptions of science and whether they feel they could make more meaningful contributions in the future.

[4] https://www.crowdcurio.com

5 Conclusion

Scientific crowdsourcing, or “Citizen Science”, is a form of research collaboration involving members of the public, or citizen scientists, in scientific research projects to address real-world problems. In this paper, we presented a set of pedagogical agents designed to guide citizen scientists in understanding the lifecycle of the research question while simultaneously learning how the crowdsourced task should be correctly performed. In addition, we have proposed a particular set of research questions as well as an experimental design for answering these questions. By conducting the proposed experiment, we will be able to better assess whether or not the proposed system facilitates public involvment at higher levels of participation within the traditional citizen science process.

5.1 Future Work

Peer Agent vs. Peer Citizen Scientist The basis for the Peer agent proposed in Section 3.2 was a purely autonomous intelligent tutoring system that facilitated learning for a particular worker. One alternative to the integration of a Peer agent is allowing multiple citizen scientists or some arbitrary number of peer agents and real citizen scientists to participate together within the same learning session. The notion of allowing crowd-workers of all types (*i.e.*, paid and voluntary) to work together is an exceptionally understudied topic despite being introduced into the literature nearly a decade ago [17]. For this reason, it is difficult to determine the value in allowing multiple crowd-workers to learn within the same environment, but is an open question beyond the scope of this course.

Cooperative Peer vs. Competitive Peer Thus far, we have introduced a intelligent tutoring system that is composed of 6 pedagogical agents, one of which plays the role of the peer. In Section 3.2, we outlined the functional responsibility of the peer with the goal of acting cooperatively with the student. However, we did not in any way discuss the notion of a *competitive peer agent*, or an agent that competes with user in some way related to the learning process (*i.e.*, arriving at the correct solution fastest). After all, this may happen naturally if two ‘real’ peers were introduced into the same learning session with the proposed set of pedagogical agents. The literature on intelligent tutoring systems tells that changing the behavior of the peer agent would certainly change the dynamic of the learning environment in either a positive or negative way [22]. Nevertheless, it would be telling to study how the change in peer agent goals affect certain aspects of citizen scientists, such as participant engagement and interest in the scientific topic.

Scientific Agent Personas As mentioned in Section 4.1, one interesting research question centers around the persona of the agents and how attributes of personas affect learning experiences. In this paper, we did not discuss the notion of agent personas in any depth, but it is still important to consider the persona that agents have *by default*. With any citizen science project, there is always an affiliated science team. For example, with the overwhelmingly popular Galaxy-Zoo project, there is a team of astrophysicists who are publicly affiliated with the project. One immediate and tractable solution could be attaching naive personas (*i.e.*, name and a photograph) to the agent. Understanding the effectiveness in choosing to model the agent personas on affiliated scientists would require an entirely different and calculated experiment, but it is certainly a topic of interest for future work.

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