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A Proposed Model for Smart Tutoring System for Biological Sciences

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Abstract

From the informatics perspective, smart tutoring systems (STSs) are intelligent computer tutors and are based on the artificial intelligence (AI) methodologies, concepts and theories. Hypotheses derived from these theories can inform curriculum, pedagogy, and efficient roles for using computers in improving educational process. STSs can adjust its tutorial to the student's knowledge, strengths, weaknesses and experiences Moreover, automatic generation of exercises, questions and tests is an important feature of STS. In addition, it may even be able to carry on a natural language dialogue.

The aim of this paper is to discuss a model for smart tutoring system for biological sciences. This paper presents a study of the technical issues for developing the STSs for biological sciences, namely: intelligent authoring tools and case-based reasoning (CBR). The obtained results can help biological researchers, and digital learning practitioners in software domain who want to be aware of new trends about developing robust smart tutoring and learning systems in the areas of life sciences. Moreover, the paper discusses the challenges that are facing knowledge engineer and developers in biological domain.

Keywords : Artificial Intelligence, Biological Knowledge representation Case-Base Reasoning, Smart Tutoring Systems and Modern Biological Education..

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1. Introduction

Combination of artificial intelligence (AI) paradigms and educational technologies results in developing robust products of smart educational software for all tasks and domains [1]. A lot of research has been conducted in the past few decades to investigate a wide variety of intelligent methodologies and techniques to develop smart educational systems. With AI methods and algorithms , new smart generation of tutoring systems and intelligent authoring tools can be created .STSs must organize their knowledge in a lesson-oriented manner. This organization must be dynamically adjusted by the system according to student models. Additionally, STS enhances instructor productivity, enabling them to cope with generating more complex training systems required to provide higher skill levels to today's high-tech trainees. It also provides tailored instruction and remediation, while allowing flexibility in teaching methods, achieving many of the same benefits as one-on-one instruction [3, 4].

In the recent years, cognitive informatics, machine learning, computational intelligence, and data mining techniques are increasing interest in the community working on smart tutoring systems [3,6,7,8] .Educational systems integrate these intelligent paradigms to improve their knowledge to allow a flexibility, versatility and sensibility to learners. More generally, machine learning approaches can be used to achieve the main three objectives: to learn the domain knowledge, to infer the student model and to integrate appropriate pedagogical rules. Moreover, recent advances in Internet technology provide a unique opportunity to distribute training across multiple sites while dramatically reducing travel-related training costs. So, software vendors and researchers start research in order to put the STSs on the internet for the purpose of distance education through the web [1,10]. Not only do students receive training at their own sites, but instructor monitor students' progress from a distance, and course authors maintain and update training material across the Internet.

In this paper we focus our discussion around the recent trends of the STSs. Section 2 presents a brief account on the main techniques of knowledge management and representation which are usually used in developing the knowledge bases of the STSs. Section 3 gives a brief overview of the general architecture of STS. The benefits of the case-based reasoning methodology for developing the STSs are discussed in section 4. Section 5 discusses the ontological engineering paradigm in Smart Tutoring Systems .Section 6 presents the technical features of STSs authoring tools. Section 7 is dedicated to proposed model of case-based STS. Finally, Section 8 summarizes the paper and raises some conclusions.

2. Artificial Intelligence In Education

Artificial Intelligence (AI) is based on many disciplines such as: computer science, cognitive sciences, philosophy, psychology, mathematics, library sciences, biology, linguistics and engineering. The goal of AI is to develop intelligent software models of the human behavior, i.e. the abilities of thinking, hearing, walking, talking, and also feeling. The field covers many research areas, e.g. action and perception (vision, robotics, auditory scene analysis), reasoning methodologies, cognitive modeling, connectionist models, constraint satisfaction, distributed AI, machine learning, knowledge management and engineering, learning, natural language processing, and planning [1,2] .The main AI technologies include: general problem-solving, expert systems, natural language processing, vision, robotics, and games. Figure 1 shows Interdisciplinary Sciences of Artificial Intelligence, in which biological sciences play pivotal role.

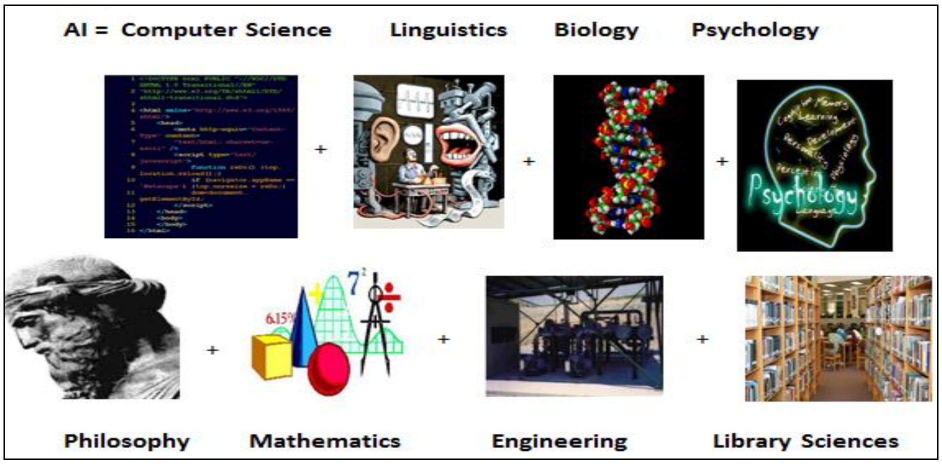
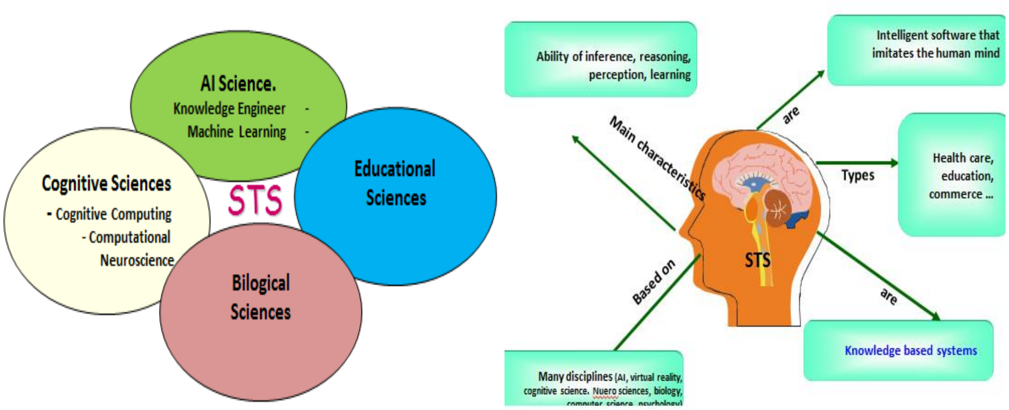


Fig.1. Interdisciplinary Sciences of Artificial Intelligence

In the recent years, cognitive sciences, AI sciences and knowledge engineering paradigms are increasing interest in the community working on developing biological smart tutoring systems [3,6,7,8]. Figure 2a shows multidisipliary filed of research of STS and 2b shows its general techical characteristics and features. Educational systems integrate these intelligent paradigms to improve their knowledge to allow a flexibility, versatility and sensibility to learners. More generally, machine learning approaches can be used to achieve the main three objectives: to learn the domain knowledge, to infer the student model and to integrate appropriate pedagogical rules. Moreover, recent advances in Internet technology provide a unique opportunity to distribute training across multiple sites while dramatically reducing travel-related training costs. So, software vendors and researchers start research in order to put the STSs on the internet for the purpose of distance education through the web [1,10]. Not only do students receive training at their own sites, but instructor monitor students' progress from a distance, and course authors maintain and update training material across the Internet.



[a] [b]

Fig.2. General features of smart tutoring systems

ITSs are smart computer tutors and typically have an expert model, student model, instructional module, and interface.

- STSs can adjust its tutorial to the student's knowledge, experience, strengths, and weaknesses. It may even be able to carry on a natural language dialogue.
- Automatic generation of exercises and tests is an important feature of ITS.
- ITS must organize their knowledge in a lesson-oriented manner. This organization must be dynamically adjusted by the system according to student models.

3. Knowledge management and representation techniques for STS

The two main parts of any AI-based educational software are (1) a knowledge base and (2) an inference system. The knowledge base is made up of facts, concepts, theories, procedures and relationships representing real world knowledge about objects, places, events, people, etc. The inference system or thinking mechanism is a method of using the knowledge base, that is, reasoning with it to solve problems.

Concerning to the knowledge base, there is a variety of knowledge representation and managing techniques are used including logic, lists, trees, semantic networks, frames, scripts and production rules [10, 11]. Figure 3 shows the different knowledge and representation approaches, schemes and techniques.

1) Logic is a set of rules and procedures used in reasoning. There are two basic types of reasoning (1) deductive and (2) inductive. In deductive reasoning, general premises are used to reach specific inferences. Propositional logic is a system of using symbols to represent and manipulate premises, prove or disprove proposition, and draw conclusions. Predicate calculus is a system of using symbols to represent and knowledge in the form of statements that assert information about objects or events and apply them in reasoning.
2) A common way to represent hierarchical knowledge is to use lists. Hierarchical knowledge can also be represented visually with graphs called trees.
3) Another knowledge representation scheme is semantic networks that use circles called nodes that represent objects or events. The nodes are interconnected with lines called are that show relationships. As an example ,figure 4. semantic network for **“Nucleic Acids".**
4) Schemas are knowledge representation methods that can deal with stereotyped knowledge. Frames and scripts are the two types of schemas. Frames are used to represent facts about object and events. Details are given in sub-elements called slots.
5) Scripts describe knowledge that is a sequence of events or procedures. Frames and scripts permit a system to infer details of specific common objects and events.
6) One of the most commonly used knowledge representation methods is production rules. Production rules are two part statements with a premise and a conclusion. They also may state a situation and corresponding action. Rules take the form of an **IF-THEN statement** such as: ***IF Animal has hair, AND animal produces milk, THEN animal is a mammal***.
7) Probability and certainly factors are numerical methods that help to reason with ambiguous and uncertain knowledge.

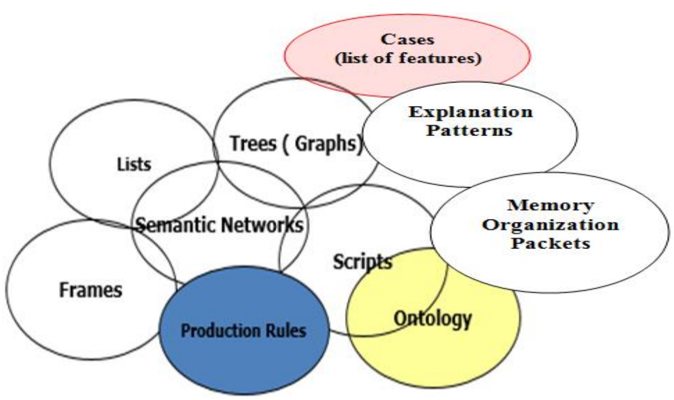


Fig.3 Knowledge Representation Schemes and Techniques

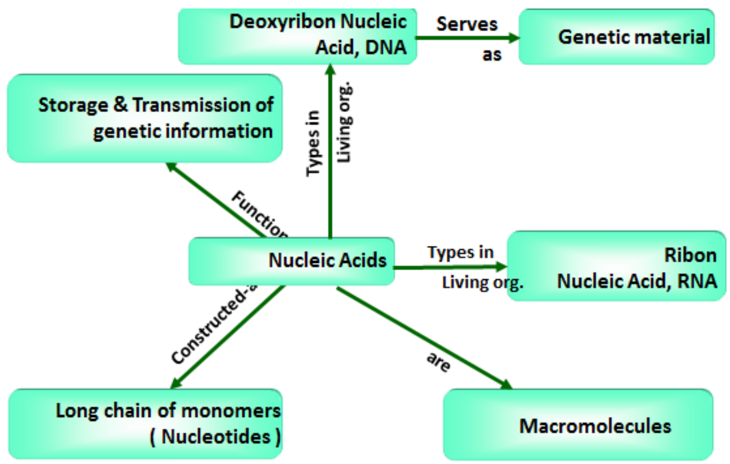


Fig.4 Semantic Network for "Nucleic Acids

Regarding the inference engine, there are many methodologies and approaches of reasoning, e.g.; automated reasoning, case-based reasoning, commonsense reasoning, fuzzy reasoning, geometric reasoning, non monotonic reasoning, model-based reasoning, probabilistic reasoning, causal reasoning, qualitative reasoning, spatial reasoning and temporal reasoning (see figure 5). In fact these methodologies receive increasing attention within the community of artificial intelligence in education [1, 2, 3].

Fig.6. shows examples for detecting brain cancer through IF-THEN reasoning technique and of liver cancer "case" of old Egyptian women.

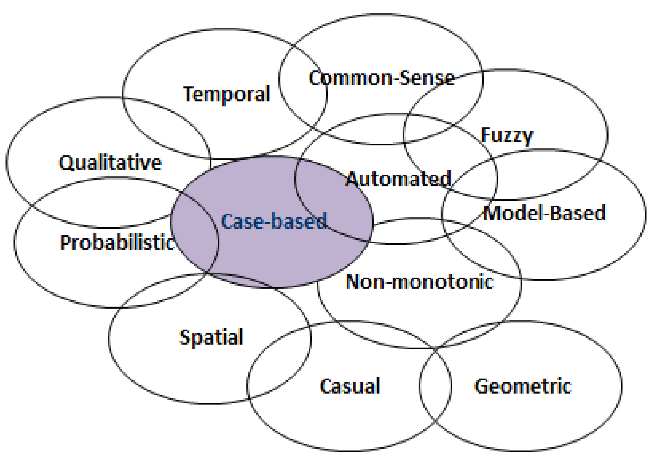


Fig.5. Reasoning methodologies within the knowledge engineering and machine learning communities

Rule1: If the symptom is changes in bowel habits, or
The symptom is unusual bleeding, or
The symptom is thickening lymph
Then cancer is infecting
Rule2: If cancer is infecting, and
The symptom is severe headaches, and
The symptom is seizures
Then brain cancer
Rule3: If brain cancer
Then treatment can be surgery
Rule4: If brain cancer
Then staging can be anaplastic.

Patient: 65-years old, female, not working, with nausea and vomiting.
Medical history: cancer head of pancreas
Physical Exam: tender hepatomgaly liver, large amount of inflammatory about 3 liters, multiple liver pyogenic abcesses and large pancreatic head mass.
Laboratory findings: total bilrubin 1.3 mg/dl, direct bilrubin 0.4 mg/dl, sgot (ast) 28 IU/L. sgpt (alt) 26 IU/L.

Fig.6. Example of **" liver cancer case"** of old Egyptian women

4. General Architecture of STS

STSs do not only describe knowledge, but they are also able to applicate and test learned knowledge. Figure 7 illustrates the main components of STS. Student modeling is used to derive an explanation for the student actions. The most important models are: stereotypes overlay models, enumerative theories of bugs, reconstruction of bugs, generation of bugs and combinations of the pervious methods. Teaching methods module plans the dialogue with the student with didactic background. The natural language user interface is important for the acceptance of the system. So, it should be very good designed to keep the motivation high, some STS programs use hypermedia to make them more attractive. Another importance is the use of knowledge base that makes the system able to follow the student in a very flexible way. Most STS work on procedural, for example mathematical domains, but a lot of work has been done in classification (diagnostics) problem solving. Solving classification problems does not require selection of one or more solutions for a given subset of observations, but also request additional observation the can improve quality of solutions.

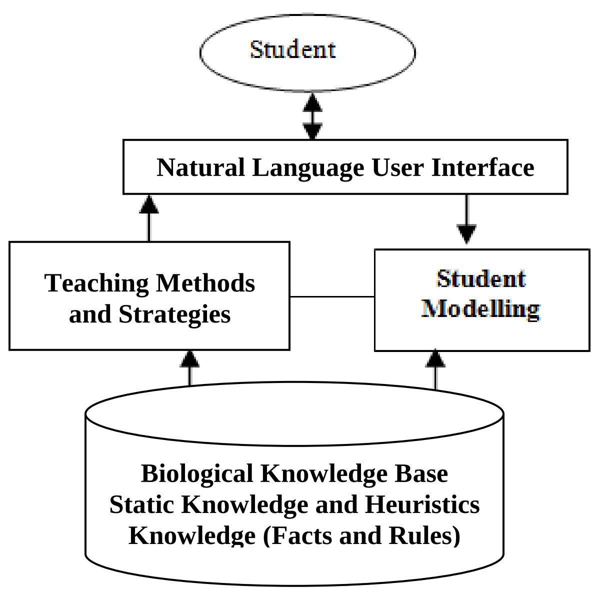


Fig 7. Main components of Smart Tutoring System

5. The Case-based STS

The new generation of STS uses the case-based reasoning (CBR) approach for inference tasks. The CBR based systems uses an extensive case-based of exercises and examples to teach students. The case-based smart tutoring systems solve new problems by adapting solutions that were used for previous and similar problems [12, 13, and 14]. The idea of case-based reasoning is becoming popular in developing STSs because it automates applications that are based on precedent or that contain incomplete causal models. In a rule-based ITSs an incomplete mode or an environment which does not take into account all variables could result in either an answer built on incomplete data or simply no answer at all. Case-based methodology attempt to get around this shortcoming by inputting and analyzing problem data.

The methodology of case-based STS can be summarized in the following steps:

1) The system will search its Case-Memory for an existing case that matches the input problem specification.
2) If we are lucky (our luck increases as we add new cases to the system), we will find a case that exactly matches the input problem and goes directly to a solution.
3) If we are not luck, we will retrieve a case that is similar to our input situation but not entirely appropriate to provide as a completed solution.
4) The system must find and modify small portions of the retrieved case that do not meet the input specification. This process is called "case-adaptation".
5) The result of case - adaptation process is: a completed solution, and also, generates a new case that can be automatically added to the system's case-memory for future use.

Research reveals that students learn best when they are presented with examples of problem-solving knowledge and are then required applying the knowledge to real situations. The case-base of examples and exercises capture realistic problem-solving situations and presents them to the students as virtual simulations, each example/exercise includes:

- A multi-media description of the problem, which may evolve over time,
- A description of the correct actions to take including order-independent, optional, and alternative steps;
- A multi-media explanation of why these steps are correct;
- The list of methods to determine whether students correctly executed the steps;
- The list of principles that must be learned to take the correct action.

The technology of CBR directly addresses the following problems found in rule-based approach.

(a) Knowledge Acquisition: The unit of knowledge is the case, not the rule. It is easier to articulate, examine, and evaluate cases than rules.

(b) Performance Experience: A CBR system can remember its own performance, and can modify its behavior to avoid repeating prior mistakes.

(c) Adaptive Solutions: By reasoning from analogy with past cases, a CBR system should be able to construct solutions to novel problems.

(d) Maintaining: Maintaining CBR system is easier than rule-based system since adding new knowledge can be as simple as adding a new case.

6. Authoring shells and STS

Authoring shells allow a course instructor to easily enter domain and other knowledge without requiring computer programming skills [7]. The authoring shell automatically generates an STS focusing on the specified knowledge. It also facilitates the entry of examples/exercises, including problem descriptions, solutions steps, and explanations. The examples may be in the form of scenarios or simulations. It allows organized entry of the course principles and the integration of multi-media courseware (developed with well-known authoring tools) which includes descriptions of the principles or motivational passages. In addition to course knowledge, the instructor specifies pedagogical knowledge (how best to teach a particular student), and student modeling knowledge (how to assess actions and determine mastery).

Some tools were meant for select authors or students and others were designed for a wide set of authors. Some tools were designed to work with a limited area of domain expertise, and some were designed for a wide range of domains. Some tools had one main instructional strategy, but others had many. Each tool had their own way of representing the student’s knowledge and understanding of the material being taught. Some tools generated instruction directly from domain knowledge. Some relied on pedagogical knowledge about the domain to create instruction. Some provided simulation environments for practice and exploration. [6].

7. A proposed model for case-based STS

Figure 8 shows the architecture of our proposed model of smart tutoring system based on CBR approach. The system helps students to analyze and repair their solutions. The student inputs a description of the domain situation and his (her) solution and the system can recalls cases with similar solutions and presents their outcomes to me student. Also attempts to analyze the outcomes to provide an accounting of why the proposed type of solution succeeded or failed. The tutoring Case-based module can perform each of the following:

1) Compose lessons at various levels of knowledge by following the curriculum.
2) Solve and generate problems.
3) Generate teaching material.
4) Critique solutions.
5) Explain anomalous situation.
6) Generate a Web page.

The web pages module was developed as one of the parts of the system. For each case in the case memory there is a web page. The generated pages are linked according to explicit or implicit relations.

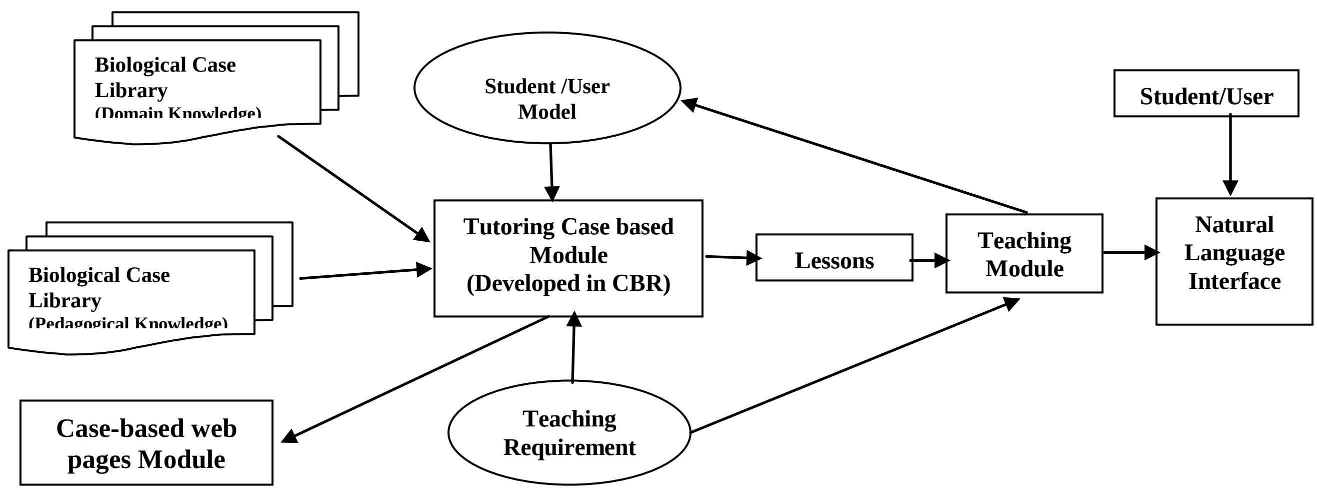


Fig 8: The proposed Architecture of Case-Based Tutoring System

8. Discussion, challenges and conclusions

1) STSs are complex to build and complex to maintain. The STS face the knowledge-acquisition difficulty. Productivity of STS development is determined by the efficiency of their knowledge representation techniques and reasoning methodologies. The key of the success of such systems is the selection of the knowledge representation scheme that best fits the domain knowledge and the problem to be solved. That choice is depends on the experience of the software and knowledge engineers.
2) Case-based reasoning methodology deals with episodic knowledge in terms of "cases" of past problems and their solutions. Such knowledge structure organizes the knowledge in a lesson-oriented manner as well as the automatic generation of tests and exercises. In STS, CBR is used to (a) compose lessons at various levels of knowledge by following the curriculum, (b) solve and generate problems, and (c) generate teaching material. Moreover, CBR addresses the problems found in rule-based smart tutoring systems, e.g. knowledge acquisition, performance, maintenance, and adaptive solutions.
3) Ontologies' usage in smart educational systems may be approached from various points of view: as a common vocabulary for multi-agent system, as a chain between heterogeneous educational systems, ontologies for pedagogical resources sharing or for sharing data and ontologies used to mediate the search of the learning materials on the internet. Moreover, software agents can understand and interpret the messages due to a common ontology or the interoperability of the private ontologies.

4) Intelligent authoring shells allow easy development and maintenance of (STS) which are based on pedagogically sound instructional strategies. The software is domain-independent and thus useful for creating a wide array of intelligent tutoring and training systems for a variety of domains.

5) The convergence of AI and Internet of Things (IoT) technologies is enabling the creation and implementation of the intelligent internet-based training technology. Such combination will provide a unique opportunity to distribute training across multiple sites while dramatically reducing travel-related training costs. Not only do students receive training at their own sites, but instructors monitor students progress from a distance, and course authors maintain and update training material across the internet.

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