Methods and Standards for Research on Explainable Artificial Intelligence:

Lessons from Intelligent Tutoring Systems

William J. Clancey
Robert R. Hoffman
Institute for Human and Machine Cognition

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ABSTRACT

The DARPA Explainable AI (XAI) Program focused on generating explanations for AI programs that use machine learning techniques. This article highlights progress during the DARPA Program (2017–2021) relative to research since the 1970s in the field of intelligent tutoring systems (ITS). ITS researchers learned a great deal about explanation that is directly relevant to XAI. We suggest opportunities for future XAI research deriving from ITS methods, and consider the challenges shared by both ITS and XAI in using AI to assist people in solving difficult problems effectively and efficiently.

INTRODUCTION

Providing explanations has been a research topic in Artificial Intelligence since the earliest expert systems [29]. This article focuses on AI programs whose operation derives from methods of machine learning, especially "deep neural networks," in a research effort referred to as Explainable AI (XAI). In particular, our analysis is based on the research projects in DARPA's 2017–2021 XAI Program, which pursued this hypothesis: "By creating new machine learning methods to produce more explainable models and combining them with explanation techniques, XAI aims to help users understand, appropriately trust, and effectively manage the emerging generation of AI systems" [15; see also 20]. This knowledge may facilitate appropriate use of AI tools, such as enabling the user to cross-check and complement automated operations to accomplish a broader activity. Providing explanations is one way to assist people in gaining this capability.

What are the best ways to explain complex systems such as computer programs? Can we facilitate people's understanding by promoting self-explaining? What pedagogical approaches should computer-based tutoring systems use, and should they be derived from studies of teachers interacting with students? These were among the questions driving AI research in the field of Intelligent Tutoring Systems (ITSs) since the 1970s [30, 31]. We illustrate ITS methods with Sharples et al.'s MR Tutor system [28], which uses statistical analysis to interpret and relate features of medical images. In MR Tutor, "explanation" is framed as an *instructional activity* for learning how to carry out a diagnostic task using an AI program as an aid. The following sections outline how models in the MR Tutor and other ITS systems are created and used. We then compare XAI and ITS research objectives and methods.

OVERVIEW OF INTELLIGENT TUTORING SYSTEMS

Intelligent Tutoring Systems research—more broadly known as the field of "AI and Education"—has been concerned with individualized instruction in many different domains, with a variety of representational media and interactive methods [12, 30, 36]. Studies show that ITS systems work, and they can work quite well at teaching STEM topics compared to teacher-to-student tutoring [1, 33]. Furthermore, although the original ITS systems of the 1970s and 1980s were often conceived as substitutes for human teachers or tutors [19], they have also been designed as tools to assist in classwork and for independent learning [28].

ITS work can be traced to the 1960s with the development of AI programs that represent objects and their relations in *structured "symbolic" models*, especially semantic nets, production rules, and schemas/frames [12, 19]. Programs using such models could solve problems such as answering factual questions and solving puzzles. Subsequent research in the 1970s added a reasoning module that interprets a structured knowledge model (aka "domain model" and "knowledge base") in particular situations for professional tasks, such as diagnosis, planning, design, and process control; these programs were called "expert systems" [7, 10].

In general, an *intelligent tutoring program* contains such an AI problem-solving program, using it to interact with and instruct a student. Thus, ITS is contrasted with computer-based instruction programs that do not have a built-in, general capability to solve the problems that are presented to students [9, 12, 19]. Furthermore, intelligent tutoring programs engage the student in a learning activity, often in the form of a dialogue [6, 32, 35], in which the program serves as an instructor. The interactive, instructional design is usually based on a theory of the pedagogical process [3, 13, 30, 31, 36].

ITS research has been concerned with teaching mathematics [1] and basic science [32, 34], as well as professional expertise relating to complicated systems, such as electro-mechanical troubleshooting [3], engineering operations [21], and medicine [9, 23]. Insofar as machine learning programs are complicated systems, and we want users to understand their capabilities and practical application, the techniques and lessons from ITS research and development over nearly 50 years are worth considering for adoption in XAI research.

COMPARISON OF ITS AND XAI APPROACHES TO EXPLANATION

The most obvious distinction between ITS and XAI programs in general is that ITS programs manipulate and interpret three essential models: 1) the formalization of what is to be learned (*domain model* [9, 12]); 2) hypotheses about the user's knowledge and cognitive activity (*student model* [8]); and 3) a pedagogical method (e.g., applying a *curriculum model* [18]).

XAI programs attempt to help users learn—which is after all the intent of providing explanations—but without having similar models and interactive capabilities. In effect, ITS and XAI researchers have proceeded with different perspectives on the learning activity, the nature of explanation, the structure of the domain model, importance of understanding the user/student's mental model and reasoning method, and following a comprehensive pedagogical plan for instructing the student. We briefly consider each of these aspects here.

Learning Activity and Instructional Setting

In general, a student is presented by an ITS program with some question or problem that he or she must solve—a form of "learning by doing." More recent ITS research has explored different kinds and aspects of a learning activity: the *setting* (e.g., "job-embedded" tutors; museum displays); *media* (e.g., web-based presentations; virtual worlds with role-playing simulations; animated agents); *instructional mode* (e.g., "collaborative inquiry"); *human-machine interaction* (e.g., recognizing and conveying emotion; speech understanding); *theories of learning*, a central theme in the "learning sciences" (e.g., cognitive processes, situated learning, apprenticeship); *educational data-mining* (e.g., learning patterns from web-based databases of student performance); and *supporting teachers* (e.g., calling attention to a student requiring remedial work). Examples can be found in broad, retrospective surveys [31, 36].

In particular, Woolf [36] surveyed recent perspectives about ITS applications, emphasizing interactive approaches in which the student is not just a passive recipient of instruction, aka "active learning." Similarly, Clancey and Soloway [13] edited a journal, *Interactive Learning Environments*, which also emphasized theory-based design of an instructional setting and the role of interactively examining and manipulating media in the learning process.

The Nature of Explanation

XAI research generally assumed at first that "explanation" only involves the process of providing an explanation to the user, on the assumption that an explanation consists of text or a graphic that is good and sufficient in itself. But ITS research clearly demonstrated how explanation must be understood from the user's perspective as a *learning process*, and thus from the program's perspective as an instructive process (which includes explaining) rather than a "one-off," stand-alone question-answer interaction [6, 9, 35, 36]. This is true whether the learning process is an activity involving a person and machine, a group of people, or process of self-explanation by a person or program.

For some XAI applications, explanation will be part of an activity that extends over multiple uses and interactions; in particular, a neural network program provided new data will continually evolve. XAI researchers have thus begun to consider ways in which the user can explore how the AI program works and its vulnerabilities (a concern ignored by ITS programs that focus on textbook knowledge [27]). Systems developed by DARPA XAI Performer Teams of UC-Berkeley, Raytheon/BBN, and PARC support some form of explanation-as-exploration. Systems developed by Texas A&M team and the University of Texas-Dallas team provide some capability for the user to engage in explanation-as-interaction.[1]

ITS research demonstrated that "explanation" is an interaction among people, the artifact, and their activity in a task context, often involving people working in teams [31]. In particular, the format/medium, content, and timing of explanations may differ to support different information needs for different roles and tasks. In critical, time-pressed situations the only practical support may be directing a person's attention; in activities over hours or days, such as long-term care for a patient, the program may serve more as an assistant in constructing situation-specific interpretive models and action plans.

The process of instruction, including explaining, necessarily involves shared languages and methods for communicating. The earliest ITSs demonstrated some form of natural language capability, such as mixed-initiative question-answering, case-method dialogue, Socratic discourse, or customized narrative presentations [6, 19, 32, 35]. ITSs have also used graphic presentations and animated simulations to convey relationships and causality [21]. Similarly, a consensus has emerged among XAI researchers that the explanation process must involve the exchange of meaningful information (versus explanations in terms of formal computational structures and processes) [20].

Domain Model

The domain model is a representation of the subject material to be taught. Generally, this model represents some process or system in a well-structured, computationally interpretable form. This is a defining characteristic of "symbolic AI"; such models are variously described as qualitative, relational, and/or semantic. Clancey [7] presented evidence that all expert systems were "model-based." In effect, a fundamental contribution of expert systems research has been to extend modeling formalisms beyond mathematical constructs in conventional science and engineering to include qualitative/relational models and associated modeling operations [10, 34].

By design, an ITS domain model can be interpreted to solve problems presented to the student. This model represents the knowledge to be learned: facts, formalisms, causal processes, and reasoning processes (e.g., a diagnostic strategy). Typically, the program that applies the domain model to solve problems is called the *inference engine* (e.g., a rule interpreter). When applied to particular circumstances (e.g., a patient's history and symptoms), it produces a (partial) solution called a *situation-specific model*.

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[1] University of California-Berkeley—https://www2.eecs.berkeley.edu/Research/Areas/AI/; Raytheon/BBN—https://www.bbntimes.com/technology/explaining-outputs-of-algorithms-with-the-help-of-explainable-artificial-intelligence; PARC—https://www.parc.com/blog/explainable-ai-an-overview-of-parcs-cogle-project-with-darpa/; Texas A&M University—https://people.engr.tamu.edu/xiahu/research.html; University of Texas-Dallas—https://cs.utdallas.edu/tag/explainable-ai-xai/.

At first, most ITS researchers viewed the domain model as being isomorphic to stored structures and subconscious processes in the brain [30]. This assumption motivated much productive research in which the ITS creates a model of the student's knowledge and reasoning. In recent decades, models have been viewed more often as *scientific tools* that are constructed and applied to understand and manipulate processes and systems in the world [11, 27], exemplified by the student model in an ITS.

Various XAI Program teams have used structured domain modeling methods to enhance the explainability of their original machine learning program. For example, the CAMEL program developed by Charles River Analytics et al. [17] provided explanations for a convolutional neural network, using a causal model (directed graph) that enabled the user to pose counterfactual questions, such as, "What is the most likely change to the observed situation that would have changed the agent's action?"

User (Student) Models

The student model represents the student's knowledge relative to the domain model, in both general and situation-specific forms [8]. The student model may be constructed using the overlay method (student model is a subset of the expert domain model), the misconception/bug method (student behavior is matched against variants/incorrect domain model), or a machine learning method [22].

Some systems can also infer the student's ongoing approach to solving a problem, such as a diagnostic strategy. ITS programs infer the student's model by asking (e.g., "Do you believe X causes Y?") or by interpreting reasoning steps. Misconceptions can also be pre-enumerated in the program and available for matching against student behavior [30, 32]. The creation of models of student knowledge and reasoning remains an ongoing concern in ITS research.

Given the focus and challenge of transforming or augmenting machine learning programs to create an explainable domain model, an early assumption in the DARPA XAI Program was that requiring researchers to also incorporate a student model was a bridge too far. But XAI research conducted to date has been a reminder that explanations need to be tailored—somehow—to the knowledge and goals of the user [24]. Indeed, "adapting to the needs of individual students" was an original motivation for incorporating AI methods in teaching programs [30, p. vii]. It is certainly unacceptable to assume that the user's understanding of the task is the same as that of the researchers [25]. Accordingly, research to develop explanation capabilities requires post-experimental cognitive interviews. For example, the Oregon State University XAI project demonstrated how to use cognitive interviews to reveal the users' mental models [16].

On the other hand, the neural network learning method addresses perceptual cognition, which was finessed in symbolic AI, the representational foundation of ITS research. When images are involved, they are usually presented to the student as text, in terms of already abstracted categories (e.g., the morphology of cultured organism is a "rod"). When the focus is image interpretation itself (e.g., x-ray interpretation [23]), manually annotated images are presented to the student (e.g., [14]). MR Tutor [28] is a relevant exception in the domain of Magnetic Resonance Imaging (MRI). Experts used a predefined ontology of features (the "image description language," IDL) to label images, and neural network learning was used by the program to relate patient cases (Figure 1).

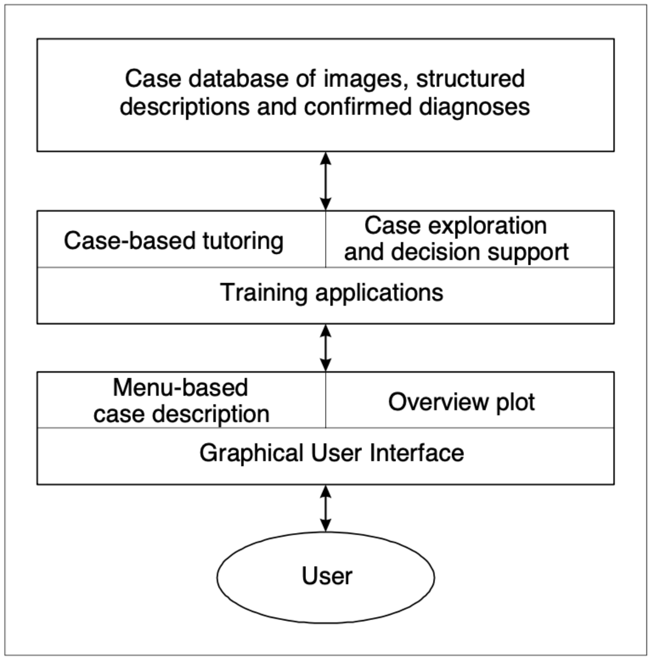

Figure 1. System architecture of the MR Tutor

> *"[The instructional] modules request images and structured descriptions from the case archive and interact with the user through a common graphical interface. The basic operation is that a) the user explores the case archive, b) either the user or the computer selects a case for teaching, c) the user describes the case using the terminology of the IDL and receives tutorial feedback from the system." (Sharples, et al., 2000, p. 5)*

The "typicality" model, created by neural network learning of patterns among the expert-labeled images, enabled the student to view the distribution of disease features across cases, and for the tutoring program to select appropriate problems and examples from the library ([28], pp. 5–8). However, MR Tutor explanations are limited to relating cases, rather than explicating the underlying causal processes that give rise to the observed morphologies—a capability required by specialists for recognizing and discriminating atypical manifestations of a disease.

Studies of radiological expertise revealed an ability to recognize rapidly and automatically "varied normal anatomy" coupled with an ability to describe "abnormal appearance" ([28], p. 3–4). By extension, use of neural network tools for practical applications, a primary objective of XAI research [15, 20], may require people to attain similar capabilities to distinguish discrepant features of interest from normal variation in appearance. Training users—and by implication explanations facilitating their learning—could be oriented accordingly by presenting normal and abnormal examples and ordering them within a cognitively justified instructional strategy, that is, a pedagogical method.

Pedagogy

Some developers of XAI systems have recognized the need for XAI systems to have a pedagogical foundation (e.g., Raytheon/BBN and Rutgers University projects[2]). However, most XAI programs do not base explanations on an explicit model of the instructional process involving structured methods of interaction (which in turn is based on a theory of how people learn). By analogy to ITS, an XAI program should incorporate a model for evaluating and instructing proper use of the associated AI program.

Early ITS systems that incorporated pedagogical models include Guidon [6, 9] and Meno-Tutor [18, 35]. The RadTutor [2] for diagnostic interpretation of mammogram images is based on *instructional principles* (multiplicity, activeness, accommodation and adaptation, and authenticity) and *methods* (including modelling, coaching, fading of assistance, structured problem solving, and situated learning).

The designers of MR Tutor formulated the following requirements for a computer system to train people in image processing (quoted from [28], p. 4):

- Base the training on a large library of cases representative of [image processing] practice;
- Provide a means of making rapid comparisons between cases by similarity of diagnostically relevant features [the role of the machine learning program];
- Expose the trainee to cases in an order that promotes understanding and retention;
- Help the trainee to make rapid, accurate initial judgements;
- Help the trainee to integrate fragmentary knowledge into more general structural schemata;
- Help the trainee to reflect on experience gained and to integrate general and situated knowledge;
- Be implemented on a personal computer, for use as part of self-study at home or work.

Also applicable to image categorization in general is the idea of a domain-specific description language of categories and terms adopted by a community of practice. In MR Tutor, the Image Description Language (IDL) included *functional descriptors* (e.g., lesion homogeneity, lesion grouping, interior patterning), and *image features* (e.g., visibility, location, shape, size, intensity).

We hypothesize that analogous conceptual categories and feature descriptions are used by people for interpreting images in general, either formally as standards within a discipline, or informally by individuals developing their own conscious method for interpreting and classifying images. The use of such feature languages in a variety of domains suggests that comprehending and trusting AI program interpretations, a primary objective of XAI systems, requires an image description language that conforms to the natural language used in the domain.

Furthermore, instructional research based in cognitive studies suggests that the chain model:

[XAI generates explanations →
User comprehends the explanations →
User performance improves]

is far too simple—it ignores the active aspect of learning, especially self-explanation. Self-explanation improves learning whether it is prompted or self-motivated [4, 5, 26]. In general, XAI programs do not facilitate self-explanation. Initial instructions given to participants provide some

[2] Rutgers University—http://license.rutgers.edu/technologies/2019-023_explainable-decisions-of-algorithms-using-examples.

explanatory material and may support the self-explanation process; but not all XAI projects provide such instructions. Although some of the projects present examples and tasks that permit the display of the AI program's boundary conditions (e.g., what the AI gets wrong, false positives), placing the user in a self-explanation mode, XAI methods have not generally exploited the person's *active efforts* to construct an explanation of the AI system.

CONCLUSION

Some scientific contributions are common to XAI and ITS research. Both seek to promote people's learning through automated interaction and explanation. Both represent processes as formal models and algorithms in a computer program, in application domains relevant to DoD concerns. Both have found that explanations are more productive when people can respond to them interactively (e.g., by asking follow-up questions), involving theories about when and what kind of explanations facilitate understanding. Researchers in both areas also recognize the need for pilot studies to evaluate the instructional methods and procedures for assessing user understanding.

XAI research has potential advantages for application to instruction, going beyond ITS capabilities. Using a symbolic problem-solving model (the embedded expert system), many ITS programs can solve new cases, but for pedagogical effectiveness, most use a curriculum of solved problems curated and organized by specialists (i.e., a "case library"), based on an ontology that has been established within the technical domain (e.g., MR Tutor [28]). It would be advantageous to couple the MR Tutor's ability to identify related cases with the ability of neural network systems to add solved cases to the library.

Another advance is the concern in XAI research with the development of appropriate trust and reliance. Research has demonstrated, for instance, that global explanations of "how the system works" alone do not consistently promote trust [19]. ITS research usually focused on teaching people to solve problems themselves, rather than teaching them how to use an AI program that assists them in carrying out complicated technical activities. The concern of global explanations is conveying broader design considerations, such as a program's strategy for selectively presenting information to prevent overload and how using a program conforms to operating policies and complies with regulations.

In conclusion, the objective of the XAI research program—to develop computational aids to promote practical use of an AI tool, including promoting a user's understanding of the tool's capabilities and vulnerabilities in practical situations—is inseparable from the objectives of ITS research involving domains of professional expertise, such as medicine, electronics troubleshooting, and engineering. We described the principles of ITS design, in which an explicit pedagogical strategy is based on a cognitive theory of learning in the domain of interest, which is expressed in a model of the subject material. That is, in ITS the design of "explanation systems" is guided by *a well-developed scientific framework*, formalized in process models of problem solving, learning, and communication that, ideally, fit people's practices. We conclude that it will be productive for XAI researchers to view "explanation" as an aspect of an instructional process in which the user is a learner and the program is a tutor, with many of the attendant issues of developing a shared language and understanding of problem-solving methods that ITS research has considered over the past 50 years.

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