A DEVELOPMENT FRAMEWORK FOR A CONVERSATIONAL AGENT TO EXPLORE MACHINE LEARNING CONCEPTS

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ABSTRACT

This study aims to introduce a discussion platform and curriculum designed to help people understand how machines learn. Research shows how to train an agent through dialogue and understand how information is represented using visualization. This paper starts by providing a comprehensive definition of AI literacy based on existing research and integrates a wide range of different subject documents into a set of key AI literacy skills to develop a user-centered AI. This functionality and structural considerations are organized into a conceptual framework based on the literature. Contributions to this paper can be used to initiate discussion and guide future research on AI learning within the computer science community.

KEYWORDS

Machine learning, visual editing, construction, neural nets, artificial intelligence

1. INTRODUCTION

Online discourse in cyberspace (mainly textual data) raises methodological problems, including data collection and coding (Vieira, Parsons, & Byrd, 2018) when it comes to analyzing it. It is often not enough to measure users' cognitive engagement only by observable indicators, but combining quantitative data and qualitative content analysis will provide more reliable results (e.g., Atapattu, Thilakaratne, Vivian, & Falkner, 2019). Therefore, this study presents an automatic discourse analysis approach using a language modeling technique called 'Neural Word Embeddings' (Word2vec) (Mikolov, Sutskever, Chen, Corrado, & Dean, 2013) to detect users' active participation in discussions in cyberspace.

This study examines the use of a chat agent with four consecutive AI modules, as well as testing machine learning and information representation. This study provides a design framework for a program related to training content. While previous knowledge of chat agents and other factors can affect a user's ability to understand, the basic assumption is that all users can benefit greatly from the interaction with the agent and chat. Within this context, the following ideas are based on:

1. Collaborating with the agent helps to increase participation in the whole process.
2. Agent recognition and training content lead to user learning and understanding of how machines learn.

DOI:10.5121/mlaij.2021.8301

2. RELATED WORK

When it comes to human-technology relations there are various theoretical frameworks (Heersmink, 2012) which share the basic idea that technical objects are projections or extensions of human organism "by way of replicating, amplifying, or supplementing bodily or mental faculties or capabilities" (Lawson, 2010, p. 2).

With the growing scale of text data, discourse analysis has become a key application area of user analytics and data mining. While the number of exact duplicates and shares of a message can be used as a proxy for popularity, discovering and grouping together multiple messages making the same claims in different ways can give a more accurate view of prevalence. The ability to group claim-matched textual content in different languages would enable fact-checking organizations around the globe to prioritize and scale up their efforts to combat misinformation.

Semantic textual similarity (STS) refers to the task of measuring the similarity in meaning of sentences, and there have been widely adopted evaluation benchmarks including the Semantic Textual Similarity Benchmark (STS-B) (2017; 2016; 2015; 2014; 2013; 2012) and the Microsoft Research Paraphrase Corpus (MRPC) (Dolan and Brockett, 2005). The STS-B benchmark assigns discrete similarity scores of 0 to 5 to pairs of sentences, with sentence pairs scored zero being completely dissimilar and pairs scored five being equivalent in meaning. The MRPC benchmark assigns binary labels that indicate whether sentence pairs are paraphrases or not. Semantic textual similarity is a problem still actively researched with a dynamic state of the art performance.

Also, given the recent developments in AI, for instance, today's natural language processing systems have come a long way toward solving many different problems, such as translation, text generation, and question-answering on specific problems. Yet, the AI community still hasn't solved the problem of creating agents that can engage in open-ended conversations without losing coherence over long stretches. Such a system requires more than just solving smaller problems; it requires common sense, one of the key unsolved challenges of AI. To give a specific example, the General Language Understanding Evaluation (GLUE) benchmark, developed by some of the most esteemed organizations and academic institutions in AI, provides a set of tasks that help evaluate how a language model can generalize its capabilities beyond the task it has been trained for. Yet, if an AI agent gets a higher GLUE score than a human, it doesn't mean that it is better at language understanding than humans. According to the influential AI scholar Mitchell, capturing such knowledge is the current frontier of AI research. As Mitchell states, while we still don't know the answers to many of these questions, a first step toward finding solutions is being aware of our own erroneous thoughts to develop more robust, trustworthy, and perhaps intelligent AI systems.

To give some examples, Google's Teachable Machine [4] provides a web page where users can train the image classification system while TensorFlow provides a playground to collaborate, train, and test an in-depth neural learning net.

- *Learning with AI:* While most AI educational programs are the latest in a long line of ideas, the idea of introducing people to AI ideas began to work with Seymour Papert and Cynthia Solomon using the LOGO program and the Turtle robot [3, 5, 7, 9]. It has served as the basis for much of the current work. Many platforms teach AI by having an individual program in block-based languages including Cognimates [23], Machine Learning for Kids [29, 17] and eCraft2Learn [27]. Other platforms introduce AI within the context of robots, such as Popbots [19, 21], as well as performance enhancements [3] and MIT App Inventor AI Extensions [13, 17, 19].

- *Learning with Conversational Agents*: Conversation agents are also used for learning, often as intelligent educators and learning friends [5]. The structure of these communication systems varies greatly, from incorporations and results based on the text [6] to integrated agents that can express emotions [7].

Researchers exploring how to engage younger students in design activities involving AI [4] identified five "major ideas" of AI to guide the development of standards:

1) "Computers detect the earth using sensors";
2) "Agents maintain models / representation of land and use it for consultation";
3) "Computers can learn from data";
4) “Making social media agents is a major challenge for AI engineers”; and
5) "AI applications can affect society in both positive and negative ways" [13]].

The model development starts with the following questions about AI:

What is AI?

Explaining what AI can confuse even experts [16,12], as the term has changed over the years. Nilson describes AI as "that work dedicated to making machines smarter ... [where] intelligence is the quality that makes a business more efficient and foresight" [10]. However, Schank notes that the definitions of intelligence may vary depending on the investigator and their approach to understanding AI [16]. He suggests that there are two main objectives of AI research - "building a smart machine" and "finding a kind of intelligence" [16]. He then proposed a set of features that included common "intelligence" - communication, knowledge of the world, internal knowledge, purpose, and art - emphasizing that the ability to read is the most important factor in intelligence [16].

What Can AI Do?

While AI has been able to find patterns in the amount of data, perform repetitive tasks, and make decisions in controlled environments, people now live better in many tasks that require art, emotion, information transfer, and social interaction.

How does AI work?

A better understanding of how AI works can help people build more sensible types of programs they work with. For this and other reasons, much of the research available on AI education in university and K-12 environments focuses on informing how AI works.

Cognitive Systems

Cognitive systems - or AI systems are rated after ideas about the human mind [4] - are used in a variety of application domains, including WordNet, IBM's Watson, expert systems, and cognitive educators. Most comprehension program messages cover topics related to information representation, planning, decision making, problem solving and learning.

Cognitive systems use many techniques for planning, decision-making, problem-solving and learning. Users may not need to understand all of these strategies in detail, but a higher understanding of how computers make decisions can help in interpreting and understanding the algorithms [29].

Machine Learning

Many students think that computers think like humans and want to make connections between human perceptions of understanding and machine learning [12]. Students are also often surprised that ML requires human decision-making and is not self-inflicted.

Research suggests that one of the ways to eliminate students' misconceptions about ML is to get involved in integrated integration. Sulmont et al. while others suggest that students develop physical algorithms to understand them in a practical way [4,6,12]. This technique has also been used in CS education [2]. In general, AI manual testing has been used as a means of implementing a variety of AI education programs (e.g. [4]), including projects where students can train ML models to analyze their movements and gestures [4,14].

Robotics

Understanding that AI agents can physically act on and react to the world is an important prerequisite for understanding robotics. Learning about sensors and their capabilities (one of the “big ideas” of AI [13]) can also aid in understanding how AI devices gather data and interface with the world.

This study provides the development of a platform and curriculum around the three “Great Ideas” in AI, as it directs ideas that have a major impact on making people understand about AI [3]. At the same time, these ideas also allow people to explore the use of a visual chat interface. The three ideas are:

- *Representation and Consultation:* People are expected to understand how the agent learns and represents new information. The agent generates two different visuals to indicate the representation of the information.

- *Conceptualization:* The agent also demonstrates the concept of how machines classify ideas. Individuals witness instances when the agent might succeed or fail in its learning and make attempts to correct it.

- *Social Impact:* The curriculum emphasizes the moral and social impact of the AI community through structured dialogue and reflection on the impacts of larger image environments.

Agent platform is a visual web connector that can be linked to a web browser and people engage with the agent in a chat in a small setting led by a personal facilitator.

3. PROPOSED MODEL

This study examines the use of a chat agent with four consecutive AI modules, as well as testing machine learning and information representation.

It takes into account what roles conversations per se appear to play as part of information exchange.

- *Conversations as Revealment:* One significant role of conversation from an information retrieval perspective is to allow the two parties to reach an understanding as to what is required by the user, and what the answerer knows.

- *Initiative and Engaging Behavior:* A number of authors have studied how a “virtual human” should behave [6, 38]. For instance, Traum et al. describe desirable aspects of a system conversing with human-beings, such as being real-time and incremental as utterances are formed over time [36]. Mixed initiative refers to both the human and the system having initiative at different points in time [1, 10, 25]. For instance, the agent may take initiative to clarify or elicit information from the user whenever appropriate, while allowing the user to drive the conversation at other times.

Recently, Christakopoulou et al. [9] studied whether to ask absolute or relative questions, comparing the utility of each for learning about users. They also asked questions contextually, based on what is already known. that characterize the solution space and allowing the user to express and modify their criteria. In each back and forth step in a conversation, the system provides some information to the user, and the user responds. Existing approaches are summarized in Figure 1.

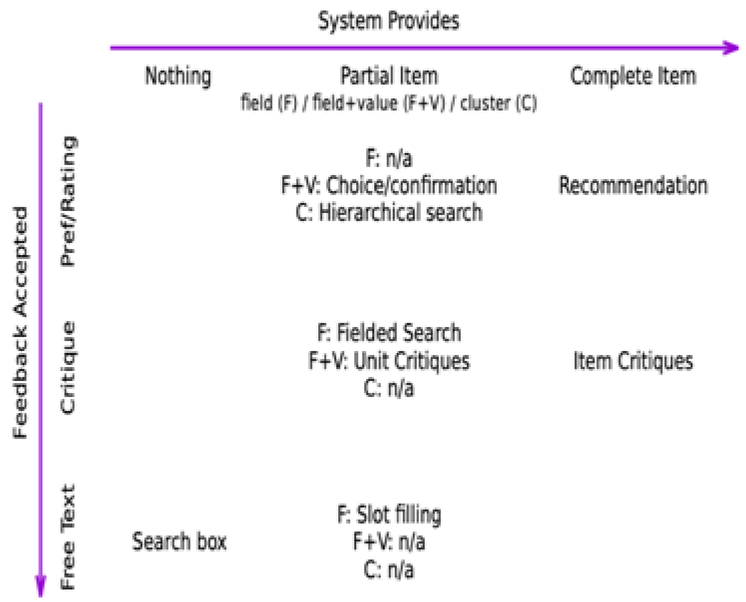

Figure 1. Conversation action space

The simplest design would be for the user to provide either a binary or ordinal score in response to a question, or a preference given two or more choices.

A more sophisticated feedback from the user would be a critique [23, 28] that indicates in what way the item or partial item presented by the system does not represent the user’s information need.

The most detailed level of feedback a user may provide would be free text. Each of this would typically fall into a single cell as indicated in the Figure 1.

As seen in Figure 1, the system may provide three types of feedback, and expect three types of responses in return. Each cell describes related work that falls into the appropriate category. Many of the partial item field (F) or field+value (F+V) interaction approaches are often considered variants of faceted search. Let's now describe each of the labeled cells in turn:

Null System - Free Text User

This is the starting point for most information retrieval systems such as Web search engines, and often for conversational systems where the user may specify many possible requests (such as commercial intelligent agents including Siri). The user is simply presented with a search box into which any query can be entered.

Partial Item System - Pref/Rating User

A user may be presented with partial information about matching items in various ways. The most common approach is for a conversational system to confirm a slot that has been inferred, such as "you are looking for a sushi place, correct?".

Some systems may also cluster items, asking for a preference. For instance, it might ask "would you prefer to a fancy restaurant, or an inexpensive one?".

A third interaction mode, where a preference is elicited over a set of (feature,value) pairs would for instance "would you prefer a laptop with a 12 inch screen for $1000, or a laptop with a 14 inch screen for $1200".

Partial Item System - Critique User

In the simplest case, fielded search provides users with a selection of known fields and users may select or specify ranges for any property they desire. This is common in online shopping scenarios, where often the allowed field values are pre-specified. In other settings a user is presented with specific individual facet values. Some commercial intelligent agents allow users to clarify in this way, rather requiring a simple yes/no.

Partial Item System - Free Text User

When a system asks a user to fill in a particular aspect of an information need, this is usually referred to as slot filling. As an example, some travel systems require users to specify travel details to complete a structured query over a public transit schedule.

Complete Item System - Pref/Rating User

Classic approaches to recommendation often request ratings of items to learn a user model for further recommendations. These may be absolute rating requests ("how much did you enjoy the movie Kill Bill?") or preference requests ("did you enjoy Kill Bill or Pride and Prejudice more?").

Complete Item System - Critique User

In this case, a system may select a given item, then allow the user to refine their information need anchoring of the properties of the item. For instance, Reilly et al. [28] describe a system where users are presented with an item and possible ways the information need can be refined. Users may select a pre-defined rich critique that allows the system to move closer to the user's goals.

Regarding the use of semantic analysis tools for feedback and conversation, the strength of Latent Semantic Analysis (LSA) to measure text similarity has been demonstrated in many research studies (e.g., Chen, Chen, & Sun, 2010; Sung, Liao, Chang, Chen, & Chang, 2016). Sung et al. (2016) used some articles to construct a latent semantic space with 250 dimensions and the LSA was used to compute the semantic similarity between pairs of sentences, such as user summary, expert's summary, or the source text. On account of the concept of new versus given information is related but distinct from the concept of text similarity, Hu, Cai, Louwerse, Olney, Penumatsa, and Graesser (2003) adapted the standard LSA and proposed the LSA based measure called a span method to detect given and new information in written discourse.

3.1. Conceptual Framework

This paper explores a ML based method based on a reward model for discourse analysis which is used to reveal the process of interaction and knowledge construction, investigate user behaviors and discourse content, and acquire deeper understanding of engagement in collaborative learning (e.g., Peng & Xu, 2020) by breaking the problem into two parts:

(1) learning a reward function from the feedback of the user that captures their intentions and
(2) training a policy with reinforcement learning to optimize the learned reward function.

In other words, we separate learning what to achieve (the 'What?') from learning how to achieve it (the 'How?'). We call this approach reward modeling.

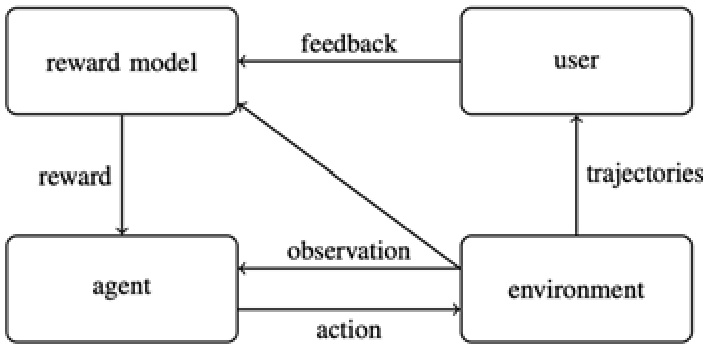

Figure 2. Schematic illustration of the reward modeling setup

Figure 2 illustrates the basic setup in which a reward model is trained with user feedback and provides rewards to an agent trained with RL by interacting with the environment.

As we scale reward modeling to complex general domains such as language modeling techniques, there can be various challenges. A reward model is trained to learn user intentions by means of feedback provided in online communities and provides rewards to a reinforcement learning agent that interacts with the environment, in this case, the social media platform. Both processes happen concurrently, thus the model is being trained with the user in the loop.

Consider this simple existence proof: let H be the set of histories that correspond to aligned behavior- aka relevant post content- in a social media setting If the set H is not empty, then there exists a reward function r such that any corresponding optimal policy $\pi *$ produces behavior from H with probability 1.

A trivial example of such a reward function r rewards the model every few steps if and only if its history is an element of the set H. In theory we could thus pick this reward function r to train our RL model. However, in practice we also need to take into account whether our reward model has enough capacity to represent r, whether r can be learned from a reasonable amount of data (given the inductive biases of our model), whether the reward model generalizes correctly, and whether the resulting behavior of the RL model produces behavior that is close enough to H.

3.2. Overview of AI Modules

Based on the reward modeling, the AI curriculum consists of four modules: "Do You Know the Agent?", "Teaching a Lawyer", "Machine Witnessing", and "AI and Ethics". Before entering the first module, individuals learn to communicate with the agent through an introduction, where the agent greets and talks with them.

Part 1, “What Does the Agent Know?” introduces people to represent information and consultation using mind maps. The representation method used is a mind map or “mind map”, which people can analyze to find relevant attributes. Positive attributes (existing) are shown as blue circles, and negative (missing) circles are shown as red circles. Users can also analyze the corpus given by the agent to create mind maps, and thus draw connections between natural language sentences and related mind map details.

In the next module, Module 2, "Teaching Agent", individuals are assigned the task of providing the agent with data on selected subjects. People can give the agent any information about a topic they would like to find. This enables them to put AI learning experience into their knowledge and interests. Agent works as an AI with minimal knowledgeable information, and users help an agent create mind maps on each topic. The concept map concept is presented in Module 1 and is based on the following modules.

Module 3: "Machine learning", is where users look at the learning process and the agent's thinking. They ask the agent to make a guess based on a previously taught concept and the agent calculates the similarity of the words in each concept by using words that represent the words representing the agent ideas and showing these schools using a bar graph. It is important for users to understand why and why the agent may be incorrectly guessing by drawing a link between similarities within Module 2 mind maps and Module 3 scores, and how to use this link.

In the final module, Module 4, "AI and Ethics", facilitators lead a discussion on how data negotiating agents and data-learning agents are used in society with both positive and negative outcomes. These discussion questions are divided into the Learning Resources section. Users can think of situations where the agent makes mistakes, and then be asked questions such as, "Will the agent know if what we are teaching is right or not?" and “How would you feel if an agent found out something wrong with you?”. The purpose of this section is to empower users with AI design tools with ethical principles. The study also aims to test users on the social consequences of mistakes made by AI, and how they can reduce injuries (Payne 2019).

3.3. System Design

The system is designed to be easy to use. It can be used using any browser anywhere you have internet access. The main features of the program are (1) a speech synthesizer, (2) a speech identifier, (3) a semantic parser, (4) a word map classifier, and (5) a website visualizer, as follows:

1. Speech amplifier: This section includes the voice of the agent using the Web Speech API. It should be noted that a particular word from the visual interface of speech recognition should be chosen so that it is not as gender neutral as possible. (A common advice is to refer to the agent as “it” instead of “he” or “she”.)

2. Speech identifier: This section converts user speech to text using the Web Speech API.

3. Semantic parser: This section performs natural language processing using NLTK [29, 32, 17, 18] and CoreNLP tools (Manning et al. 2014). The NLTK toolkit works with words, while the CoreNLP toolkit renders parts of speech [30] and processes sentences obtained from speech recognition. The adjective performs the following three functions used in each function.

a) Name identification: As a job introduction, the agent asks people for their name and location. The relay conveys the input received after each query, removing all nouns, proper nouns, and foreign names. The specified name or location is the appropriate last name seen.

b) Subject Identification: In the first module, the tester identifies which user the question is asking. Since the number of ideas that the agent is aware of is limited, the examiner searches for these ideas. When a familiar concept is found, the parser retrieves the identified concept and a pre-programmed mind map is displayed to users. These mind maps are created offline using a third-party explorer capability.

c) Mind Map Builder: In Modules 1 and 2, the agent demonstrates his / her knowledge of ideas and words on mind maps that are generated according to sentence structure and speech components. An adjective identifies a field of concept for the interaction between descriptive words and a topic (e.g., a negative interaction between water and desert), and then sends this information to a web browser.

4. Classifier: This section classifies the word by comparing word representation using NLTK's Wordline Interface (Loper and Bird 2002; Fellbaum 1998). In each sense, all the descriptive words are compared to each other. Once the similarity between all pairs has been calculated, the overall similarity between a concept and topic is its weighted average similarity score. The classifier returns a normalized score for each topic, denoting the topic with the highest similarity score to be the topic that the concept relates to.

5. Visualizer: This section creates mind maps and histograms based on pre-defined sentences and user-defined sentences using D3.js [15, 25].

To show how the parts fit together, in the introduction, the system prompts the user to speak; sends a user voice response to a browser-based speech recognition, which converts the response into text; stores text response to user location session data; sends a text response to a server-based server, processing the text for important details; returns the processed information to a browser-based speech compiler, which causes the agent to speak, causing the user to speak again; and repeats the process until it ends the conversation.

Figure 3. includes a view of the histogram, which shows similarities between the concept and the sentence of the title.

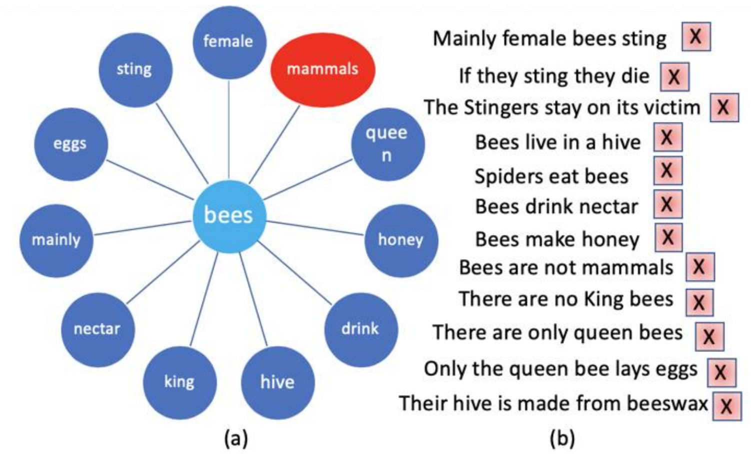

Figure 3: (a) Mind map composed of sentences in (b). This is shown in Module 2 on the agent's website. (b) Users of sentences have informed the agent during the study.

4. RESULTS AND DISCUSSION

To measure system performance, a small pilot study can be done to determine if people understand the visual representations. Once hired people can hear about the three different perspectives on information representation (Modules 1 and 2) and the three different machine learning perspectives (Module 3) shown in Figure 4.

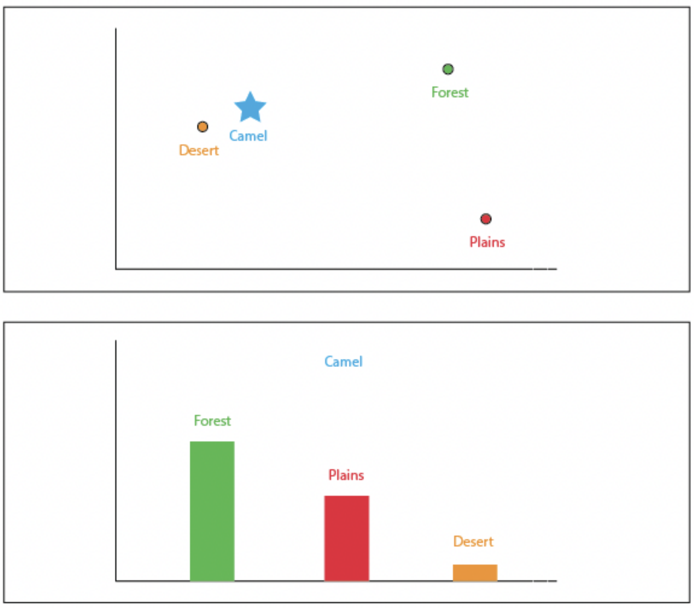

Figure 4: As shown in the orange bar in this histogram view, the agent can guess which concept will affect it.

Testing can also be done even if the knowledge of the learning platform and the content of the training improves people's understanding of how machines represent information and learn. Specifically, the level of user engagement can be assessed by measuring the number of sentences used in the conversation with the agent, and whether it corresponds to their level of understanding.

A consistent test protocol can be followed at different times. The size of the session can be from one to four, each with a facilitator. First, researchers can randomly test participants' information on voice assistants such as Siri and Alexa via icebreaker. After this, they can conduct a pre-follow-up test for the agent (Figure 5). Modules 1 to 4 must then be completed respectively. All work will last ~60-80 minutes depending on the length of the conversation. People should do all the tests individually on paper and without the slightest distraction from the investigators. In addition to the measurement data from the test, researchers can also perform video recordings of the time, participants in log sentences contribute and record users' responses to test questions.

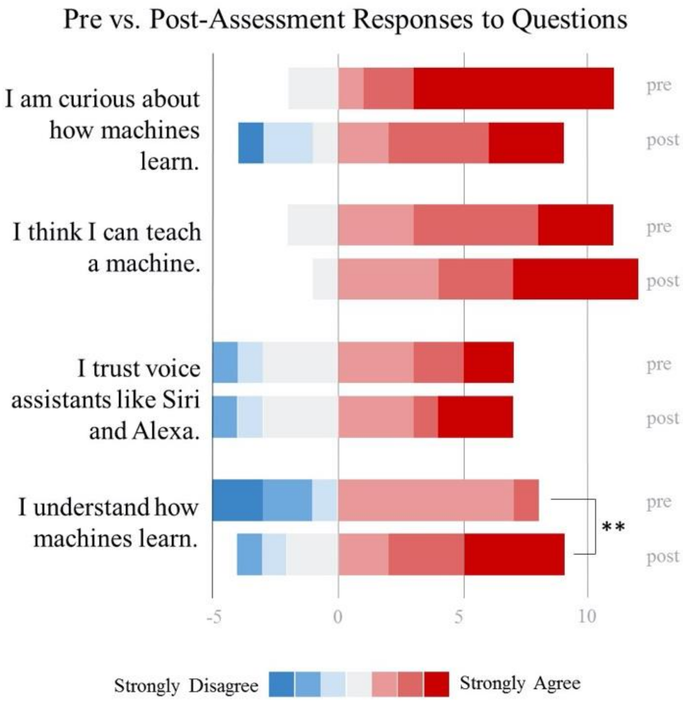

Figure 5: Sample responses to pre- vs. post-examination

Assessments

To answer the idea that people can learn effectively and to understand how machines learn, the following questions can be asked for assessment purposes:

1. What sentences can you say to the facilitator to create the following mind map in Figure 1? (This tests their understanding of how information is represented.)

2. What can you tell the agent about a particular name so that he can correctly guess the related topic? (This tests their understanding of how the agent reads.)

3. Why would an agent find it difficult to match another word to a particular topic even if he knows everything that needs to be known about them? (This is an open-ended questionnaire for examining potential mistakes an agent may make.)

4. Have you ever tried to mention the name ‘agent’ to the agent? If not, ask your tutor if you can try. Does the agent recognize its own name? If not, why not? Can you think of another name the agent would not see? (This is an open question in the agent's internal language management.)

These pre- and post-test assessments can also be used to assess individual self-awareness as an engineer and motivation to learn. People can be asked to rate how much they agree or disagree with the various statements on a scale of 1 to 5.

1. I want to know how a machine learns.
2. I think I can teach it to the machine.
3. I trust voice assistants like Siri and Alexa.
4. I understand how the machine learns.
5. The activities we have done today have been helpful in learning how machines learn. (Post-test only.)
6. The mind map of each concept and topic helped me think about the agent's brain. (Post-test only.)
7. The histogram helped me to understand how the agent made decisions. (Post-test only.)

5. CONCLUSION AND FUTURE SCOPE

This work introduces a development framework for a conversational agency that educates individuals about the representation of information and machine learning.

By training an agent, recognizing his mistakes, and retraining an agent, individuals can make sense of the intelligence of a representative. In the future, the content of the agent training should be expanded to address more topics in AI. Hopefully, this work will promote more AI training content using conversational agents and viewing tools to help individuals understand the AI algorithms.

The current framework of research has some limitations. First, it includes a small number of participants. Further testing may reinforce the claim that the agent is operating. Also, there is a need to create a future iteration of this study in which researchers can compare the performance of the visual interface of another chat agent.

Computer scientists usually rely on statistical tools to demonstrate that a particular underlying factor had a “causal” effect on the outcome of interest. While in the natural sciences, causal effects are measured using lab experiments that can isolate the consequences of variations in physical conditions on the effect of interest, more often than not, social life (including education through means of AI) do not permit lab-like conditions that allow the effects of changes in the human condition to be precisely ascertained and measured. This would merely provide evidence on *one* of the causes, which may not even be one of the more important factors. In a quest for statistical “identification” of a causal effect, scientists might often have to resort to techniques that answer either a narrower or a somewhat different version of the question that motivated the research. So, research can rarely substitute for more complete works of synthesis, which consider a multitude of causes, weigh likely effects, and address spatial and temporal variation of causal mechanisms.

For this study to be conducted, there is a need to control how participants interact with the agent by reducing their knowledge required for participants to be able to train the agent in real time.
Last, but not least, the skills and design considerations outlined in this paper will need to be expanded to keep pace with new discoveries, technologies, and rapidly changing social norms. Researchers and educators of AI, and related technology and education communities should be encouraged to both participate in intimate discussions and design considerations in this paper and use them to lead and promote artistic and future research on AI learning.

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