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Active Learning Improves the Teacher's Experience: A Case Study in a Language Grounding Scenario

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Abstract

Active Learning, that is, assigning the responsibility of learning to the students, is an important tool in education as it makes the students become engaged in and think about the things they do. A similar concept was adopted in the context of Machine Learning as a means to reduce the annotation effort by selecting the examples that are most relevant or provide more information at a given time. Most studies on this subject focus on the learner's performance. However, in interactive scenarios, the teacher's experience is also a relevant aspect, as it affects their willingness to interact with artificial learners. In this paper, we address that aspect by performing a case study in a language grounding scenario, in which humans have to engage in dialog with a learning agent and teach it how to recognize observations of certain objects. Overall, the results of our experiments show that humans prefer to interact with an active learner, as it seems more intelligent, gives them a better perception of its knowledge, and makes the dialog more natural and enjoyable.

Index Terms: active learning, language grounding, teacher experience, dialog, learning

1. Introduction

In education, Active Learning (AL) is a generic term for models of instruction which assign the responsibility of learning to the students. Such models are important as it is believed that, in order to learn, students must not only listen, but also read, write, discuss, and solve problems. By adopting AL methodologies, students not only become engaged in doing things, but also in thinking about the things they do [1].

Due to the importance of AL in education, a similar concept was adopted in the Machine Learning (ML) area [2, 3, 4]. If the learner is "curious" and actively queries the teacher for labels it needs, the number of examples required for training is expected to be lower than in a scenario in which the learner just passively "listens" to the examples provided by the teacher, which may not provide the best possible information gain. The terms learner and teacher are used in a generic sense here, as the application of AL strategies is not limited to scenarios involving interactive artificial agents.

Most studies on AL focus on its ability to improve the learning process from the perspective of the learner's performance. On the other hand, the teacher's experience has caught less attention. However, it is also a relevant aspect, especially considering that, in many cases, AL is used to reduce the human effort required to annotate a large amount of examples. In such cases, it is clear that using strategies that automatically select the most relevant examples to label leads to a better experience from the annotators' perspective, as it reduces their effort in multiple levels. However, in scenarios similar to those that occur in educational contexts, in which there is a direct dialog between the teacher and the student, it is not as clear whether AL leads to a better experience from the teacher's perspective.

In this paper, although we still analyze the learner's performance, we focus on the impact of AL on the teacher's experience in an interactive context involving natural language dialog. That is, how using AL strategies impacts the effort required from the teacher, the naturality and enjoyability of the dialog, and overall, whether the teacher prefers to interact with a learning agent that applies AL strategies. To do so, we perform a case study in a natural language grounding scenario, in which humans have to engage in dialog with a learning agent and teach it how to recognize observations of certain objects.

In the remainder of the paper, we start by providing an overview on related work in Section 2. Then, in Section 3, we describe the experimental setup of our case study, including the task, agent, and evaluation methodology. The results of our experiments are presented and discussed in Section 4. Finally, Section 5 summarizes the contributions of the paper and provides pointers for future work.

2. Related Work

Natural language grounding is typically addressed in the area of robotics as a means to bridge the gap between natural language descriptions and the corresponding observations in the environment [5]. Observation here does not refer solely to vision, but also to perceptions related to other senses, such as touch [6]. In summary, an observation corresponds to the perceptions obtained through one or multiple of the agent's sensors at a given time. In order to reduce complexity, research in this area has typically focused on scenarios featuring a small set of simple concepts, such as colors and shapes (e.g. [7, 8, 9]), or actions, such as grabbing and moving (e.g. [10, 11]). More complex scenarios are typically only considered in the context of virtual agents, which are not affected by noisy sensors (e.g. [12, 13]).

An important distinction among approaches to natural language grounding is between those which focus on continuous learning through interaction and those which rely on large datasets containing images or videos paired with the corresponding natural language descriptions. A similar distinction occurs in the context of AL between scenarios involving stream-based and pool-based sampling approaches [2]. In the former, the agent is faced with different unlabeled examples over time and, for each of them, must decide whether to perform a query. On the other hand, in the latter, it has access to all or a large set of unlabeled examples and must select those which provide the most information when labeled [4].

In the context of natural language grounding, studies in-

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volving interactive scenarios typically focus on the actual grounding of the concepts and the ability of the agent to recognize new observations of those concepts. The learning approaches used in such studies depend on the nature of the concepts to ground, but typically involve Reinforcement Learning (RL) (e.g. [9, 13]), learning from demonstration (e.g. [10]), or other semi-supervised approaches (e.g. [14, 7]). On the other hand, when relying on large annotated datasets, the approaches are typically based on overlapping occurrence and the studies also focus on other more complex aspects, such as contextual disambiguation [12], the induction of grammar rules that allow the distinction between references to actions and objects, and the generalization to other contexts and scenarios that involve different concepts [15, 11].

We selected a natural language grounding task for our case study, as is it has already been successfully paired with AL in previous studies. Furthermore, although some studies rely on precompiled datasets that pair objects with their corresponding natural language descriptions to explore AL-related aspects such as the sampling approach (e.g. [16]), most of them focus on real interactive scenarios between humans and an artificial learning agent. Similarly to research on language grounding in general, a common scenario in this context involves the learning of colors, sizes, and shapes, as well as simple objects based on those attributes (e.g. [14, 7, 8, 17]). However, there are also studies targeting other concepts, such as object manipulation actions [10], relational symbols [18], word pronunciation [19], and body poses [20].

The application of AL strategies can be split into three steps: example selection, query generation, and feedback acquisition. Example selection is typically based on information gain. That is, from the set of unlabeled examples, the learner selects those able to provide high information gain when labeled or, in other words, the ones it is less confident about. This concept can be generalized to identify the classes that are harder to recognize or distinguish, allowing an agent to request additional examples of those classes, even if they are not currently observable. Calculating the actual information gain can be done in several ways (e.g. [16]), with the appropriateness varying according to the scenario and the underlying models.

Regarding queries, the most common in studies on interactive natural language grounding scenarios are confirmation and label queries. However, there are also studies that explore the use of feature and/or demonstration queries (e.g. [10, 17]). Furthermore, the timing of the queries is also relevant, in order to not overwhelm, confuse, or completely remove control from the teacher (e.g. [7]). Still, there are studies revealing advantages of using opportunistic AL strategies in the learning process [21, 22]. That is, allowing an agent to ask questions about concepts or observations that may be off-topic for the current dialog, but that allow it to improve the ability to identify those concepts over time. This is particularly important in scenarios in which examples are only available for a limited time.

Finally, considering that the dialogs in the context of interactive natural language grounding are typically constrained, feedback is typically obtained directly from the teacher's response and/or changes in what can be observed using rule-based approaches according to the type of query.

Although many studies on interactive AL reveal less effort and more enjoyability by the teacher, only a few have delved deeper into the teacher's experience when interacting with artificial active learners. Among those, the studies in the context of the SIMON robot are the most in depth. First, AL was explored as a transparency mechanism, that is, as a means to reveal the learner's knowledge to the teacher [14]. In this study, the teachers taught the robot how to identify four different symbols using a set of three templated utterances for providing positive and negative examples and performing confirmation queries. On the other hand, the robot used non-verbal cues to answer and, in the AL scenario, to reveal uncertainty and perform label queries as well. Not all teachers were able to understand the cues provided by the agent, decreasing performance. Still, those that did revealed a more accurate perception of the agent's knowledge. However, they expressed desire for more control over the interaction. On the other hand, in the passive scenario, the teachers wished that the agent could ask questions or at least provide some additional feedback. A subsequent study [7] confirmed that a mixed-initiative approach with a fluid balance of control is preferred by the teachers. Furthermore, in the context of learning from demonstration, feature queries tend to be perceived as more intelligent by human teachers, as they are the most common among humans in that context [10]. However, good feature queries are also the hardest to generate.

3. Experimental Setup

The aim of our study is to assess whether AL improves not only the learning process of the student, but also the teaching experience. To do so, we performed a case study in a language grounding scenario. This section describes that case study, including the task, the characteristics of the agent, and the evaluation methodology.

3.1. Task

Our study focuses on a natural language grounding task, in which a human subject is expected to engage in dialog with an artificial agent and teach it how to identify observations of a selected set of object classes. More specifically, we devised a graphical interface in which the human can select images of objects extracted from the UMBC dataset [23] and textually chat with the agent about them. This way, we avoid the issues caused by noisy sensors and speech recognition, which are not the focus of our study. However, no restrictions are enforced in terms of the actual dialog.

3.2. Agent

In order to learn how to identify observations of specific objects through dialog with a teacher, an agent requires two main competences: the ability to dialog and the ability to incrementally update a recognition model with the labeled observations obtained from the interaction with the teacher.

Regarding the dialog, our agent follows the classical modular dialog system architecture (e.g. [24, 25]). However, considering that it focuses on a constrained task, many of the components are simplified. For instance, Natural Language Understanding (NLU) is reduced to intention recognition followed by object label extraction for intentions that trigger it. The agent can perform three kinds of dialog act: acknowledge, answer, and query. The first is used as a transparency mechanism [14] to convey to the teacher that the agent has grasped the concept being taught. The second is used to reply to queries by the teacher and may take different forms accordingly. The last is used to request information from the teacher and is mainly used during the application of AL strategies. It can be split into three kinds of query: confirmation queries, which aim at confirming whether an assumption by the agent is correct; label queries, which request a label for an object that is currently being observed; and demonstration queries, which request additional examples of a specific object class.

The agent's internal model of the objects is based on features obtained using the pretrained VGG-16 network [26] and applies the IKNN-SVM algorithm [27], an incremental hybrid algorithm that provides an adequate balance between accuracy and prediction time.

Regarding the application of AL strategies, considering that there are multiple object classes, the agent relies on entropy [28] for example selection. This can be used not only to perform queries when the teacher shows multiple different objects to the agent at the same time, but also to identify the object classes that are harder to distinguish and request additional examples. In this context, the agent adopts an opportunistic approach [21, 22], that is, it may perform queries regarding subjects that are not the current focus of the dialog if they are the most relevant. Although the studies on this subject revealed no impact on the teachers' willingness to interact with the agent, one may argue that such strategies may impact the flow and naturality of the dialog in scenarios involving more complex tasks or domains than those covered in the studies. Nevertheless, considering that our case study also focuses on a constrained task, we expect the trade-off to be beneficial. Still, as previous studies show that teachers prefer scenarios with mixed-initiative [14, 7], the agent only performs queries when the uncertainty or information gain is above a certain threshold.

3.3. Evaluation Methodology

Considering that our case study focuses on the impact of the application of AL strategies, we have two evaluation scenarios: one in which the agent behaves as a passive learner and another in which it behaves as an active learner. In the former, it simply interprets the teacher's utterances and replies accordingly. In the latter, it also applies AL strategies to take control of the dialog and focus on obtaining knowledge that it deems relevant.

In our study, 20 human subjects interacted with the learning agent in both scenarios. The subjects were evenly distributed in terms of age, gender, and level of education. 70% had some kind of previous interaction with an artificial agent.

Each evaluation scenario has two phases: the learning phase and the testing phase. In the learning phase, the human teacher is instructed to teach the agent how to recognize observations of three object classes of their choice among those available. There are no restrictions in terms of time nor the number of examples provided. The teacher is instructed to end the learning phase when they believe the agent is able to accurately identify the three object classes. In the testing phase, the teacher is instructed to assess the agent's ability to use the knowledge acquired in the learning phase by performing two label queries, two confirmation queries, and two demonstration queries, in any order. These target multiple ways in which the agent can use the acquired knowledge. Namely, identify the class of a given observation, check whether an observation belongs to a given class, and select appropriate examples of a given class.

To objectively evaluate the performance of the agent, we rely on accuracy. More specifically, we split it into learning and testing accuracy. Learning accuracy refers to the accuracy of the agent's internal model at the end of the learning phase when applied to all the examples provided by the teacher. Testing accuracy refers to the agent's ability to answer the queries performed by the teacher during the testing phase. In this context, we also provide the results according to the type of query.

To evaluate teacher experience and the effort required to teach the agent, we rely on two aspects. First, we compare the number of teacher turns and intent distribution between both scenarios. Second, we rely on the teachers' answers to a set of questionnaires. After interacting with the agent in each scenario, the teachers answered the following questionnaire, which is based on the one used by Cakmak et al. [7] in their study:

1. Who had more control over the agent's learning process?
2. How difficult was it to teach each concept?
3. How clear was your mental model of the agent's knowledge?
4. How intelligent did the agent seem?
5. How enjoyable was it to talk to the agent?

In the first question, the teachers had to choose among three options: the teacher, the agent, or both. In the remaining, they had to provide an answer in a five-point Likert scale. Additionally, after interacting with the agent in both scenarios, the teachers answered the following questionnaire:

1. Which agent did you prefer?
2. Which agent is more appropriate in a learning context?
3. Which agent learned faster?
4. With which agent was the dialog more natural?

In the first question, they had to choose between the two scenarios, while in the remaining there were two additional choices: both and none.

4. Results

Table 1 shows the accuracy results achieved by the agent in each scenario. The results confirm that using AL strategies improves the performance of the agent both in the learning and testing phases. However, the impact is higher in the testing phase, with an improvement of 14 percentage points, versus 8 in the learning phase. This happens because, independently of the scenario, during the learning phase the teacher is able to provide additional examples when the agent makes mistakes. For the same reason, as expected, the learning performance is higher than the testing performance in both scenarios. Looking into results for the different kinds of query, we can see that the agent had more difficulty to answer label queries than confirmation queries, as there is a larger answer space. The performance on demonstration queries is the highest as the agent was able to select examples that it had seen before.

Table 1: *Accuracy results achieved by the agent.*

	Passive	Active
Learning Accuracy	85%	93%
Testing Accuracy	73%	87%
Label Queries	62%	76%
Confirmation Queries	73%	86%
Demonstration Queries	84%	100%

Regarding the effort required from the teacher in order to teach the agent, there was a total of 532 teacher turns in the passive learning scenario and 688 in the AL scenario, which represents a 29% increase. Considering that AL is typically used as a means to hasten the learning process, this seems counterintuitive. However, it makes sense in this scenario, as the termination of the learning phase is controlled by the teacher and the queries by the agent make the gaps in its knowledge more apparent, leading to longer dialogs. Still, we have performed experiments that confirmed that, for the same number of object descriptions, a higher performance is achieved when AL strategies are applied. Furthermore, the distribution of intents among teacher turns, shown in Table 2, reveals that while the proportion of object descriptions is similar in both scenarios, there is an increase of confirmations and reduction of queries in the AL scenario. This suggests that the agent's assumptions are typically correct and that the teacher has increased awareness of the agent's knowledge.

Table 2: *Intent distribution among teacher turns.*

	Passive	Active
Description	26%	28%
Confirmation	20%	30%
Rejection	3%	1%
Clarification	2%	0%
Label Query	18%	16%
Confirmation Query	12%	9%
Demonstration Query	12%	12%
Other	7%	4%

Looking into the answers of the questionnaires, 80% of the teachers stated that they had the control of the dialog in the passive learning scenario. That number reduces to 25% in the AL scenario, with 20% stating that the agent had the control and 55% that it was shared between the two parties. Thus, it is clear that, as expected, the application of AL strategies allows the agent to take control of the dialog when necessary.

Table 3: *Classification of different aspects regarding the teaching experience.*

	Passive	Active
Teaching difficulty	2.30 ± 1.17	2.40 ± 1.43
Mental model clarity	3.70 ± 0.86	4.25 ± 0.72
Perceived intelligence	3.50 ± 1.05	4.00 ± 0.92
Enjoyability	4.35 ± 0.99	4.55 ± 0.69

Focusing on the quality of the teaching experience, in Table 3, we can see that the teaching difficulty was considered similar in both scenarios. This means that, even though the dialogs were longer and additional descriptions were provided by the teachers in the AL scenario, the teachers did not consider the additional effort to be significant. On the other hand, to some level, the teachers had a better mental model of the agent's knowledge and perceived higher intelligence from it in the AL scenario. This suggests that the application of AL strategies not only improves the agent's learning process by allowing it to focus on the examples that it deems most relevant, but also improves the teachers' experience by reducing the need to estimate what the agent actually knows and select appropriate examples.

Overall, even though the enjoyability ratings were high in both scenarios, the use of AL strategies leads to a more enjoyable experience for the teacher. This is confirmed by the results of the direct comparison questionnaire shown in Table 4. We can see that the vast majority of the teachers preferred the scenario in which the agent applied AL strategies and considered it to be more appropriate in a learning environment.

Table 4: *Teacher selections between the two scenarios.*

	Passive	Active	Both	None
Preference	15%	85%	-	-
Appropriateness	0%	100%	0%	0%
Learning speed	15%	60%	20%	5%
Natural dialog	5%	80%	15%	0%

Still in Table 4, we can see that, even though the dialogs were typically longer in the AL scenario, 60% of the teachers stated that the agent learned faster. We identify several potential reasons for these results. As previously discussed, the termination of the learning phase is controlled by the teacher. Thus, considering that in the passive learning scenario the teacher is less aware of the actual knowledge of the agent, they may terminate the learning phase prematurely and only become aware of the knowledge gaps during the testing phase. Second, considering that in the AL scenario the agent also takes control of the dialog, the teachers can be persuaded to extend the learning phase until there are no more questions from the agent. Additionally, considering that the dialog is less one-sided, the teachers may extend it simply because it is more enjoyable.

Finally, 80% of the teachers stated that the dialog was more natural in the AL scenario, which is typically synonymous with a better and more enjoyable dialog experience. Once again, this is mainly due to the shared control of the dialog, which is more common in interactions between humans. Furthermore, it is important to note that the application of an opportunistic AL strategy did not seem to impact the naturality of the dialog. However, as discussed in Section 3.2, this is mainly due to the constrains of the task and its application in broader domains requires a more careful planning.

5. Conclusions

In this paper, we have explored how AL affects the teacher's experience in the context of an interactive language grounding scenario with an artificial learning agent. This is an important aspect, as it potentially impacts the teacher's willingness to interact with artificial learners. Overall, the results of our experiments with 20 human subjects show that not only using AL strategies improves performance from the learner's perspective, but also that humans prefer to interact with an active learner, as it seems more intelligent, gives them a better perception of its knowledge, and makes the dialog more natural and enjoyable.

As future work, it would be interesting to explore scenarios that involve learning from negative examples, as that was a common request among the teachers. Thus, it as the potential to improve their teaching experience. Furthermore, it is important to perform a case study involving a more complex task and domain, in order to assess the actual impact of using opportunistic AL strategies in the flow and naturality of the dialog and how that affects teacher experience.

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