Effective Interaction Strategies for Adaptive Reminding

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Introduction

We discuss the problem of creating a reminder generation system that successfully alerts a user to daily tasks while adapting the features of its reminders to the user's reminding preferences. There are many example applications in which reminding is useful; we motivate the discussion by focusing on two such applications. The first is an office environment in which users require assistance in managing their time. Here the reminder system may be embedded in a computational agent, e.g. CALO (Mark & Perrault 2005), that assists its user in performing a set of office tasks. The second environment in which an intelligent reminding tool may be of particular use is as a cognitive orthotic for the elderly and cognitively impaired. One system that has been tested in such an environment is Autominder (Pollack *et al.* 2003).

There are a number of enhancements to these basic reminding tools that will lead to more acceptable, robust systems. Enhancements include (1) one or more justifications for each reminder, (2) the ability to modify the granularity of a reminder, (3) choosing the best audio or visual signal for reminders, and (4) learning a user's preferences for each of these reminding features and adapting the system to meet these preferences to the extent possible.

Justifications

In certain cases, a single reminder for an activity or task may not be enough to convince the user that it is the right time to perform that task. For example, consider an elderly woman being reminded by her orthotic to perform her daily 15-minute exercise routine. She may be much more likely to comply with the reminder immediately if it has been issued with the justification that her favorite television program will be on in twenty minutes. Similarly, should an office executive have a meeting scheduled in 2 hours and a brief to write with a deadline that falls within the bounds of the meeting time, that user may appreciate a reminder to write the brief with a justification accordingly attached.

Reminder Granularity

An important consideration in providing reminders to the elderly in particular is the question of the level of granularity at which to issue each reminder. Especially with persons of declining cognitive ability, reminder granularity must increase in proportion to the user's level of cognitive decline. As an example, consider an elder adult who at times requires reminding before making breakfast. Initially, the reminder need only prompt the user to "prepare breakfast," whereas in time that user may have trouble remembering the steps that must be taken to prepare breakfast, and the system can at that point jump in and provide a cue to open the refrigerator and take out the eggs, and so on. Modification of reminder granularity is also useful in the workplace: when an employee is learning a new procedure or computer system, initially a set of fine-grained reminders (i.e. a set of step-by-step instructions) may be most beneficial, and once the user becomes more competent, the level of reminding can be relaxed.

Signaling

Another issue in generating intelligent reminders is the type of signal that is used to alert the user that a reminder is being issued. Whereas some users may appreciate a loud audio signal so as to be sure that it is heard, others (perhaps those working in an office environment) may find a loud noise to be disruptive. Thus, office-based users may prefer to be reminded via an email message or a pop-up window, while another class users may prefer an audio signal (perhaps in addition to a pop-up window) to an email message, or for someone with cognitive decline, a picture might be best.

Learning

Techniques taken from the area of machine learning can effectively enhance our solutions to the challenges described above: the system can learn how best to interact with a particular user based on that user's pattern of compliance with the reminders received. Rudary et al. (Rudary *et al.* 2004) created a simulated environment in which they analyzed the effect of using reinforcement learning to assist a system in learning a user's preferences over *when* to issue a particular reminder. We hope to extend this work to incorporate the learning of a user's preferences for justifications (when and for which tasks they are effective), reminder granularity (which tasks require which levels of granularity), and audio signaling (which signals are most effective for which tasks).

In order to perform such learning, the system must rely on its interpretation of the user's environment so as to make inferences regarding whether or not a task has been performed successfully. When a task is not fulfilled, the system can evaluate the reasons behind the failure and adjust its reminding features accordingly. Consequently, we note that we will be reliant on an activity recognition system, such as (Liao *et al.* 2005; Pentney *et al.* 2006), that provides a high degree of certainty as to the user's prior and current activities.

Intended Approach

In order to address each of the challenges listed above, we must devise a plan for extending current reminder systems to incorporate justifications, reminder granularity, different signaling types, and learning. There are a number of methods that we can use in attempting to solve these problems. The first is an extension of (Rudary *et al.* 2004) in which the system relies on reinforcement signals (in the form of successful reminders, i.e. those that result in the user fulfilling the associated task requirements) to know when it has performed to the liking of the user. An alternative technique involves *supervised learning* directed by an *active learning* component through which the system interacts with its user in such a way as to learn the user's preferences through direct user feedback.

Reinforcement Learning

A *reinforcement learning* problem is one in which an agent performs actions and receives rewards, or payoffs, for performing those actions; and the agent's goal is to maximize its cumulative reward. The agent learns a *policy* regarding which action to take at each state of the world, based on an evaluation of its expected rewards. The work performed by (Rudary *et al.* 2004) focused on a reminding agent in the domain of cognitive orthotics. Their technique is interesting because it introduced a dynamic action-generation component that is tied to knowledge of a user's planned activities. More specifically, they provide their reminding system with knowledge of a user's daily activity schedule, and the system in turn generates a reminder plan based on that user's schedule.

The payoff function that they devised for their learning algorithm is fairly simple: whenever a reminder is issued, the system is awarded a slightly negative payoff so as to dissuade the system from issuing reminders when unnecessary (lest they become overwhelming to the user); an activity being successfully completed results in a large, positive payoff, and when an activity is not performed in accordance with its specification, the associated payoff to the system is very negative. So at every time point, the system acts based on its current belief as to whether issuing an immediate reminder to the user will amount to its receipt of the greatest possible rewards.

This evaluation metric can be ported to the office environment fairly easily, and it will help us to determine which feature combinations are most useful in a reminder. Different sets of reminding features may lead to different levels of user performance; for example, it may be the case that a particular user will readily respond to an email message with a coarse-grained (terse) reminder, whereas a fine-grained (multi-step) reminder in a pop-up window might be ignored by this user with all else equal. The system, therefore, will earn higher rewards for emailing this user a succinct reminder than using a pop-up window for a long reminder, and in the future the shorter, emailed reminder will be the most appealing choice in terms of payoff when the system finds itself in a simliar state (where "state" may refer to the time of day, type of activity being cued, time until earliest/latest activity start time, etc.).

Supervised Learning

Supervised learning describes the set of learning problems in which a system is provided with a set of labeled data points (called the training data) from which to base its future labeling decisions. In this context, *active learning* refers to a machine learning problem in which the learning algorithm (in our case embedded in our reminding tool) itself selects the data to present to the user for training. Previous work involving active learning of scheduling preferences (Weber & Pollack) attempted to provide the user with a number of scheduling options in order to learn a user's general ranking function over potential schedules. In the reminding domain, we can design a system to interact with its user in order to learn which reminding features are more important than others, i.e. whether the user would rather be reminded with an audio signal or an email message, a single or multiple justifications, and so on. This will speed up the initial learning phase so that the system can begin to behave to the user's liking more readily.

Summary

There are a number of dimensions to intelligent reminding that must be explored in order to create a personalized, adaptive system that is acceptable to and appreciated by its user. Enhancements to current systems include justifications for the reminders provided, the potential for reminding at multiple granularity levels, several audio and visual signaling capabilities, and the ability to learn a user's reminding preferences over the above features as well as others. Two learning techniques that we propose to explore in this context are reinforcement learning and supervised learning directed by an active learning component.

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