Gaze-based Online Face Learning and Recognition in Augmented Reality

Abstract
We propose a new online face learning and recognition approach using user gaze and augmented displays. User gaze is used to select a face in focus in a scene image whereupon visual feedback and information about the detected person is presented in a head mounted display. Our specific medical application leverages the doctor’s capabilities of recalling the specific patient context.

Author Keywords
Eye Tracking; Augmented Reality; Face Recognition; Real-time Interaction

ACM Classification Keywords
H.5.2. User Interfaces: Input Devices and Strategies, Graphical HCIs, Prototyping

General Terms
Experimentation, Human Factors, Performance

Introduction
Interaction technologies have become mobile and hence thoroughly integrated into everyday objects and activities. Embedded computing devices allow us to access digital resources in information systems more easily even in professional life. In fact, augmented reality has aroused people’s attention [1]. Recent see-
through head mounted display (HMD) technology has a great potential for the future of augmented reality. We propose a new interactive machine learning (ML) environment for them: online face learning by combining a see-through HMD and a wearable eye tracker. The combined system allows a doctor to learn new patient faces online: he or she provides the name labeling by looking at the current patient whose features are extracted in real-time. At a later stage, our face classifier functions as an "external brain" for the doctor in order to recall the specific patient.

System Description
First, the eye tracker captures the scene image in front of the doctor and computes the gaze position on the image. The image and the gaze data is piped to the face detection module and the nearest detected face to the gaze position is selected as the face in focus. Then, the face’s ML features are sent to the learning module or the recognition module (figure 1).

Learning mode
Texts are prompted in the HMD to navigate the doctor to look at the face that he or she wants to add to the face database. After a new face in focus is detected (the learning mode is contextualized), the local binary pattern (LBP) features [2] from the face images are stored in the database.

Recognition mode
The LBP features of the face in focus are extracted (similar to learning mode). Nearest neighbor (NN) search is then applied to the database in order to find the person. After checking that the doctor is looking at the same person for a while, the retrieval results are displayed in the HMD.

Learning Results
In a preliminary test, we used 5 images (n=5) from 8 different persons for training, and test images were taken in the same lighting conditions. We achieved 100% of precision rate and 68% of recall rate. This result indicates that the system performs reasonably in our context where the doctors have to detect patients in the hospital in quite stable lighting conditions for small samples. The precise recognition of 100-500 faces is the next goal.

Acknowledgements
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Learning from Conflicting MDP and Human Reinforcements

Abstract
Current approaches in reinforcement learning that combine MDP reward with human reinforcements assume both signals to be complementary. They rely on the fact that the system and the human have the same desire of how a particular task should be completed. We present the case where these reward signals are conflicting, i.e. the goals of the agent are not aligned with the interests of the human trainer. More precisely, we describe an approach how such problems can be solved by multi-objective reinforcement learning.

Introduction
Over the years, learning from humans has received a great deal of attention. In the TAMER framework [1], a reinforcement learning (RL) agent learns a combination of MDP reward and human reinforcement. This framework, and many others, assume that the desired behavior of the human trainer and the MDP reward is complementary. This means that feedback of the human trainer can be used to guide the agent in learning the optimal policy more quickly than it would in the case of relying only on the MDP reward. The overall goal of the TAMER framework is to speed up the learning process and to reduce the sampling complexity. In this paper we consider the scenario where the human and the system have different interests, which the agent has to leverage.
Conflicting rewards

Let us consider a controller for systems that interact with a human on a daily basis, such as a household heating appliance. What policy should the controller follow to operate *intelligently*? Does "intelligently" mean minimizing energy consumption or does it signify maximizing the comfort level of the user? Using the first definition, the energy bill will be minimized as the heater will rarely be turned on, while by the second definition the heater will operate almost constantly, even at moments in time when even when large increases in energy usage create negligible increases in comfort. It is clear that either of these definitions are extreme and will most likely not be what the human is looking for. Therefore, the energy consumption and the human interests are two separate, *conflicting* objectives and the human will most likely be interested in trade-off solutions that compromise these objectives. As we are dealing with systems that interact directly with the end-user, it is crucial that the learning process does not impose large discomfort on the user. Therefore, in contrast to TAMER, our setting does not aim to speed-up the learning process. We are interested in learning in collaboration with the end-user, by optimizing a performance criterion (e.g. energy consumption) while also maintaining a desired level of user satisfaction. In Van Moffaert et al. [2], we apply this idea to intelligently control office equipment, by determining appropriate schedules (on and off times). In this application, the device consists of an office espresso machine, which is often left running 24/7, especially in working environments. We learn trade-off solutions in a multi-objective RL setting by combing both MDP reward and human rewards. The MDP reward represents the energy consumption of a particular mode, which can easily be measured by appliance monitors. In a real-life situation, it is unlikely that the human will spend a lot of time and effort in rewarding the agent for satisfying actions. When the system performs 'good' for the human, he usually finds this obvious or evident behavior. Only when the system is not performing as expected, the human will intervene. Therefore, we only consider negative human reinforcements. Whenever the user is not pleased with the outcome of the system, it will let this know by manually overriding the current control policy. For instance, when the machine is turned off and a beverage is requested, the user manually overrules the agent and waits for the water to reheat. This particular intervention is considered negative user feedback, which is to be minimized in future schedules. By conducting experiments with two sets of weights on each of these two objectives, we obtain two distinct trade-off schedules, i.e. a so-called *energy-oriented* and *user-oriented* schedule. We compare them to a naive always-on schedule in Table 1.

<table>
<thead>
<tr>
<th>Table 1: The economical properties of the three schedules.</th>
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<tbody>
<tr>
<td>Hours / day</td>
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<tr>
<td>24h</td>
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<tr>
<td>Cost / year (€)</td>
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<td>Manual overrides</td>
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We see that the potential gains in economical cost of both learned schedules are significant compared to the always-on policy. As learning proceeds, we observe that the amount of human interventions decreases. Surprisingly, the number of overrides of the final policy remains quite low for the energy-oriented schedule as well, as the most busy timeslots are covered.

References


A Gesture Learning Interface for Assistive Robotics Employing a Growing Neural Gas Approach

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Abstract
Recognition of human gesture is an active area of research in the development of intuitive human-machine interfaces for assistive robotics and environmental design to facilitate aging-in-place. A framework for gesture learning is presented which utilizes arm-scale 3D gesture motions collected using an RGB-D camera. Motion samples are clustered using the Growing Neural Gas (GNG) algorithm and are mapped to desired goal configurations through user-generated feedback. Learning accelerates as untrained nodes leverage successful past outcomes from nodes in their respective neighborhoods. Alternative network distance metrics are considered in the search for probable exemplar configurations within a node neighborhood.

Author Keywords
Gesture recognition; Growing Neural Gas; aging in place; intelligent environments; robotics

ACM Classification Keywords
F.2.2 Pattern Matching, I.2.9 Operator Interfaces, I.2.10 Representations, data structures and transforms
Introduction
Gesture in the form of arm and hand gesticulation is an important mode of human communication [5]. Thus, research in this area as a means of intuitive human-machine interaction is warranted. The challenge of gesture learning is commonly divided into a set of typical problems to be addressed. These include the selection of a sensor paradigm, compact representation of data, pattern recognition, and machine learning.

The researchers envision gesture based interaction as the basis for a non-verbal communication paradigm between users and assistive robotics (Figure 1).

![Figure 1](image)

Figure 1. The non-verbal communication loop of the Assistive Robotic Table (ART) being developed by our lab at Clemson University. The focus of this work is on the communication loop of emergent (learned) response of ART to the patient.

System Framework for Gesture Interface
Using an RGB-D depth sensing camera, 3D motion samples of an actor’s left hand were collected. Candidate gestures used for experimentation include the American Sign Language representations for Come, Go, and Stop [1]. Feature vectors composed of dynamic instants [6] are extracted and clustered using GNG [3]. The view-invariant nature of dynamic instants allows a high quality feature vector to be extracted independent of sensor placement (excluding occlusion). Over time, GNG learns the topology of the user’s action space.

A novel alternative to classification is employed as each node in the action space is progressively mapped to the user’s desired 3-DOF configuration for a robotic component. The mapping does not rely on the user to emulate any choreographed gesture form and it is not a simple mimicking of user action. Rather, the robot makes a best guess at the user’s intended response to a gestured command and considers user feedback to inform future action plans.

A simple user-generated binary reinforcement signal guides the mapping process. Reference nodes in a gesture’s GNG area can be expected to map to the same response. Past rewards accumulated by a single node are indicative of its probable success as an action for a given gesture input. Within a neighborhood of nodes, one whose action has received repeated positive rewards will be emulated by surrounding neighbors. Hence, the fully trained GNG cloud becomes an associative memory [7] which allows generalization of gestures. Untrained nodes draw best guess responses from their neighbors’ past successes and thereby learn with fewer feedback iterations.

Learning Efficiency
Toward the goal of reduced user input, various distance metrics may be applied to the topology of the GNG cloud. Connections (edges) within the cloud may suggest a node’s relative usefulness in the learning process. This research compares network distance metrics including Euclidean, path length [8], clumpiness [2], and age-related resistance [4]. The
relative efficacy of these metrics is influenced by the separability of feature vectors. A tradeoff emerges between the average number of feedback steps required for convergence and the number of gestures (currently) left unrecognized due to incorrect guesses. Ongoing research will involve intelligent training of new nodes where unrecognized gestures lie in the receptive fields of previously trained nodes.

References
RobotsFor.Me and Robots For You

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Abstract
Interactive Machine Learning (IML) and Human-Robot Interaction (HRI) are rapidly expanding fields that focuses on allowing non-expert users to naturally and effectively interact and teach robots. The importance of conducting extensive user studies has become a fundamental component of this work; however, due to the nature of robotics research, such studies often become expensive, time consuming, and limited to constrained demographics. In this work we present the Robot Management System, a novel framework for bringing robotic experiments to the Web through a project known as RobotsFor.Me. We present a description of our open source system and describe the potential this and similar systems have for contributing to IML.

Author Keywords
Web Robotics, HRI User Studies, Remote Users, Crowdsourcing

ACM Classification Keywords
I.2.9 [Robotics]: Operator interfaces.; H.5.3 [Group and Organization Interfaces]: Web-based interaction.

General Terms
Design, Experimentation
Introduction
Integration of user studies into the design, development and evaluation of new Interactive Machine Learning (IML) and Human-Robot Interaction (HRI) techniques has been shown to result in more usable methods [2], whereas development of algorithms in isolation risks biasing useability towards expert users. Although user studies are shown to be effective, they are subject to limitations due to safety, robot durability, or high cost. Due to this, researchers are typically limited to using a single robotic platform for a given study and conducting user studies requires bringing human subjects in one at a time. Such studies take days to weeks to perform and are limited to relatively small numbers of participants. Furthermore, the typical research cycle progresses through the stages of method formulation, implementation, user study, and presentation of results, which integrates user studies only at the culmination of a project, leaving little time for the integration of lessons learned back into the final product.

Our work seeks to address several of the above limitations by introducing a web-based framework for HRI and IML experimentation. Recent projects have explored web-based robot control [1]; however, unlike past efforts, our work focuses on bringing research-grade robots into the homes of non-expert users. With this, we introduce the Robot Management System (RMS), a web-based framework designed to dramatically reduce the overhead of running remote user studies that involve control of the robot.

RMS and RobotsFor.Me
The Robot Management System (RMS) is an open-source framework that allows researchers quickly and easily install, configure, and deploy a secure and stable remote lab system. The framework is designed in a robot, lab, and interface independent manner. At its core, RMS is a custom content management system written in PHP backed by a MySQL database. Its main goal is to keep track of different ROS (Robot Operating System) enabled robotic environments, interfaces, users, and research studies with little need of additional programming by researchers. By doing so, such a system enables researchers to focus on the goals of their research without needing to spend countless hours testing and implementing a custom web solution.

The RMS was developed with the following goals in mind:
- Robot and interface independent design
- Support for easy creation and management of new widgets and interfaces
- Secure user authentication and authorization
- Creation, management, logging, and analysis of multi-condition user studies
- Website content management

Once the system itself is deployed, researchers can choose from existing interfaces, or create their own custom web interface such as the one depicted in Figure 1. RMS provides a customizable browser interface for robot control, integrated support for testing of multiple study conditions, and support for both simulated and physical environments. Through these capabilities, RMS enables any online user across the globe to participate in user studies by observing the actions of a robot through camera feeds and providing control commands through keyboard and mouse.

Using this system, we have deployed an instance of the RMS in a project called RobotsFor.Me. By using a RobotsFor.Me, we are able to develop, prototype, and run preliminary tests on learning algorithms, interfaces, or
other methodologies in a rapid development cycle that was previously unfeasible. Such a system has gone through an initial study to prove its validity as a form of conducting such research [3].

Robots For You
To progress IML in robotics, it is necessary to make professional grade robots and research available to the masses. Due to costs, expertises levels, and safety concerns associated with current state-of-the-art robotic platforms, using the web to conduct such studies makes logical sense. RobotsFor.Me sits as only one example of a system that aims to allow naive users to gain access to robots and participate in research studies. The efforts put into the development of the RMS allow researchers to deploy similar systems with a fraction of the overhead that was previously required. Furthermore, by allowing users access to robotic simulation environments, experiments can be in parallel and reduce the risk of naive users damaging the robot or its surroundings.

We note that the presented framework can not replace face-to-face interactions, and therefore will have limited application in some areas of research, such as proxemics or physical HRI. Instead, we envision RMS, RobotsFor.Me, and similar projects contributing to research in areas such as shared autonomy, learning from demonstration, and interfaces for teleoperation, by enabling evaluation at unprecedented scale through the web.

Acknowledgements
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Transparent Machine Learning — Revealing Internal States of Machine Learning

Abstract
This work concerns the revealing internal states of Machine Learning (ML) meaningfully so that users can understand what is going on inside ML and how to accomplish with the learning problem. As a result, ML process becomes more understandable and usable. It changes from a "black-box" to "transparent-box". A case study is presented to show the benefits of transparent ML in improving impact of ML on real-world applications.

Keywords
Interactive machine learning; HCI; Black-box; Transparent machine learning.

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous. I.2.6. Artificial intelligence: Learning.

Introduction
Machine Learning research is largely inspired by significant problems from various fields such as biology, finance, medicine, society etc.. ML algorithms offer a set of powerful ways to approach those problems that otherwise require manual solution. However, ML research field has a frequent lack of connection between ML research and real-world impact because of complexity of ML methods [1, 2]. For instance, for a domain expert who may not have expertise in ML or programming, an ML algorithm is as a "black-box", where the user defines parameters and input data for the "black-box" and gets output from its running (see Figure 1). This "black-box" approach has obvious drawbacks: it is difficult for users to understand the complicated ML models, such as what is going on inside ML models and how to accomplish with the learning
problem. As a result, users are uncertain for ML results and this affects the effectiveness of ML methods.

Our research focuses on making the ML process understandable and usable by end users through revealing internal real-time status update of ML models with meaningful presentations. Because of the leverage of internal states, ML models become transparent to users. The “black-box” ML thus becomes “transparent” ML (TML).

**Transparent ML for Interactive Feedback**

We propose that interactive ML interfaces must not only supply users with the information on input data and output results, but also enable them to perceive internal real-time status update of ML. As a result, ML process becomes a “transparent-box”.

The TML includes following steps:

- Select internal state variables that are dynamically changed and meaningful to users;
- Present the changing of internal state variables visually and meaningfully to users;
- Interact with the ML process (e.g. change ML parameters, insert records) based on transparent feedback from revealing of internal real-time status update.

TML presents selected internal states dynamically to users meaningfully (e.g. money saved, time preserved) with domain knowledge but not only using pure numbers. It provides a feedback loop that aids users learn what is going on and how to accomplish with the given learning problem. Users also have freedom to interact with the ML (e.g. insert data records or add new data features) based on the feedback in order to improve models. TML provides a means for users to assess the model’s behaviors against a variety of subjective criteria based on domain knowledge and examples. As a result, the users’ understanding and trust of the system could be improved and it benefits the accuracy of learning systems as well. Furthermore, TML allows users progressively improve the learning accuracy by modulating parameters online.

**Case Study**

Water supply networks constitute one of the most crucial urban assets. Prediction of water pipe condition through statistical modeling is a significant element for the risk management strategy of water distribution systems. In our previous work, a hierarchical nonparametric model is proposed to predict failure of water pipes. In this model, pipes are divided into $K$ groups based on laid years and modeled as a
hierarchical beta process (HBP). In the top level, hyper parameters, that control across all groups of pipes by a beta distribution, are set manually according to domain experts’ experience. Then, the mean failure rate ($q_k$) in each group can be generated from the distribution. In the middle level, the mean failure rate ($p_{i,k,i}$) of each pipe asset is generated through another beta distribution with $q_k$ as parameter. In the bottom level, the actual failures are generated from a Bernoulli process year by year using $p_{i,k,i}$.

In order to allow users better understand how this prediction works, the meaningful internal state of mean failure rate $q_k$ and $p_{i,k,i}$ are presented to users interactively. As shown in Figure 2, the top chart presents the status update of $q_k$ and the bottom chart presents the status update of $p_{i,k,i}$. During ML process, the charts are dynamically changed to reveal the internal real-time status update. To interact, users can point to any (interact detail) $q_k$ in the top chart and the corresponding $p_{i,k,i}$ is presented accordingly in the bottom chart. Furthermore, these real-time status updates can also be accessed through a displayed table as Figure 3. Compared with directly presenting the final prediction of failure rate $p_{i,k,i}$, the presentation of $q_k$ and $p_{i,k,i}$ allows users learn how the prediction of failure rate of each pipe is approached. As a result, users’ trust on predictions is increased. Therefore, TML benefits the impact of ML on real-world applications.

**Contributions of the Work**

This work contributed the approach of TML to make ML models understandable and usable by end users.

**Acknowledgements**

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Framework for Interactive Classification for Decision Support Problems

**Introduction**

Machine Learning systems for tasks such as fraud detection and surveillance deal with building classifiers that are deployed within a larger interactive system with experts in the loop. These applications involve a limited number of labeled examples with a high cost of labeling, and a large number of unlabeled examples, with majority of them being negative (skewed class distribution). Typically, once the models are trained, these systems score a large amount of new data and present the experts with a ranked list of cases to review. This manual verification is not only expensive but can also have intra- and inter-expert variability implications. The immediate goal of such interactive systems is to help the experts find relevant (positive) examples. The commonly used approaches in such skewed class distribution problems use supervised classification and focus on increasing the classifier accuracy (or related metrics). The business goal of deploying these machine learning systems is not just to maximize the performance of the classifier but also to make the experts more efficient at performing their task.

Consequently, these approaches must aim to optimize multiple criteria including the cost of labeling an instance, the utility in terms of the relevance (of highly ranked instances) to the experts (exploitation) in conjunction with (guarantees on) future utility or effectiveness (exploration).

Figure 1: Joint consideration of cost, exploration and exploitation
Interactive Learning Framework

We envision that most interactive learning systems can be mapped to this framework and use it to manage the three factors jointly. Our framework consists of the following components:

- **Exploitation Model**
- **Exploration Model**
- **Reviewing/Labeling Cost Model**
- **Utility Metric**
- **Joint Optimization Algorithm**

The exploration, exploitation and cost model can further have the following three broad variations: Uniform, Variable, Markovian. Uniform means that each example gets the same value from the model. Variable means that each example can potentially have a different value that is a function of its features. Markovian means that each example has a variable value which is not only a function of its features but also a function of previous (ordered) set of examples that have already been labeled.

Related research in this area has focused on managing one or two of these three factors at a time. Active learning algorithms [6] seek to maximize exploration (often at the expense of short-term exploitation). Traditional supervised learning algorithms maximize short-term exploitation. Cost-sensitive variations [2] of both of these aim to optimize cost and exploration (cost-sensitive active learning [4, 7]) or cost and exploitation (cost sensitive learning). Reinforcement learning is targeted at optimizing exploration and exploitation.

In this work, we propose an extension to the current interactive learning framework that encompasses all these related research areas to yield a general framework that takes into account several domain concerns in addition to the absolute measures of performance. Broadly, these concerns can be categorized into exploration, exploitation and labeling or reviewing cost. Note that these components are general and although they occur in most domains that fit into an interactive setting, the correct model for each component still needs to be selected. The learning algorithm would employ an optimization criterion that takes into account their respective models and combine them using a strategy typically guided by the application domain.

We are currently evaluating the efficacy of our proposed framework by applying it in a health insurance claims domain [3]. The goal of the system deployed in this setting is to minimize payment errors by predicting which claims are likely candidates for error, and presenting the highly scored ones to human auditors so that they can be corrected before being paid. We are also evaluating the framework on the chemo-informatics task of predicting which compounds are active against the HIV infection [1] used in Active Learning Challenge 2011, and information filtering task using 20-newsgroup dataset [5].

**Summary**

We emphasize that for an algorithm to operate efficiently in an interactive setting, multiple criteria need to be optimized. The existing approaches that focus on exploration (in isolation or typically in the context of cost) do not optimally tie the business goals of such systems with the learning strategy. Our general framework proposes different types of models for exploration, exploitation and cost criteria as well as proposes that an optimization and evaluation needs to be guided by the application domain based on an apt integration of these criteria.

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DIY Smart Home: Narrowing the gap between users and technology

Abstract
Over the past decade, we have been building intelligent systems to provide assistance for persons with dementia wishing to age-in-place [1]. These systems are built using partially observable Markov decision process (POMDP) controllers. While the POMDPs provide a framework for long-term model learning and reinforcement learning, they must be engineered to fit each situation and user to ensure adoption. Custom-building a smart home solution is a time-intensive exercise, in which technologists extract and encode knowledge from end users. As this process is neither easily understood by, nor accessible to, end users, we are exploring this problem from two complementary directions. From the user perspective, our research with older adults and family members has revealed the need for practical, customizable systems that can be set up and managed by “informal caregivers”. From the technological perspective, we have developed a method by which POMDP-based smart-home controllers can be specified at an appropriate level of abstraction using probabilistic relational modelling and a database schema for assistance systems. Our goal is to close the gap between these perspectives by designing interfaces for end-users to express contextual knowledge, needs, and preferences in a natural way to build custom smart home solutions in an organically developing, DIY (“do-it-yourself”) fashion.

Figure 1. Conceptual user interface mock-up for a sensing and control system that would enable end users to build custom, DIY (“do-it-yourself”) smart home solutions.

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Author Keywords
Intelligent systems; smart homes; machine learning; user interfaces; aging; dementia; family caregivers.

ACM Classification Keywords
H.1.2 User/Machine Systems H.5.2. User Interfaces; J.3 Life and Medical Science, K.4.2 Social Issues

Introduction
The globally aging population and rise of dementia and other chronic illnesses have motivated substantial research in smart homes to support aging-in-place. This field has focused on technological innovation to date and must now shift to understanding users’ needs and contexts to bridge solutions to real-world problems. Our research has revealed a critical need for smart homes to be customizable by end users to provide a desirable degree of user control and accommodate unique and dynamic home contexts [2]. We describe our research from two complementary perspectives and propose a DIY approach that aims to close this gap.

We argue that smart home solutions for persons with dementia will only be useful if caregivers can easily customize and manage them. Research suggests that caregivers are willing to assume such responsibilities [3; 4; 5] as long as doing so does not add extra burden or shift their focus from their care responsibilities [2]. We interpret this as the need to minimize changes to physical artefacts, interpersonal interactions, and everyday routines when devising solutions.

Effective smart home solutions should be able to sense what is happening and appropriately intervene. Traditional approaches involve designing a system for one particular application and its specific environment, tasks, and users. As this would require re-engineering for every new application, our approach is to construct abstractions to represent domain knowledge in the most natural way, such that end users will be able to use sensing and control systems to build their own custom solutions.

A next-generation DIY approach
Our user-centered research aims to uncover the language by which end users can naturally and effectively specify their own situations and preferences. Our technology-centered research aims to provide a method to encode this language into a POMDP-based smart home system that will learn and adapt to users’ needs over time. We use a probabilistic relational model (PRM) of assistance tasks that is based on a psychological theory of human-machine interaction. This theory provides appropriate “hooks” for end users to complete a relational model, creating a ground instance of a POMDP controller for each new situation [1]. Details of the inner workings of the intelligent sensing and control systems are hidden from end users, who only need to provide information at a high level. Our research is therefore focused on formalizing these abstractions. Our formal models can then be implemented to enable end users to build their own specific solutions.

The POMDP models encode an assistance task by defining the user goals, the environmental states, the user behaviours, the system actions, and the user’s cognitive abilities. These factors are derived from a task analysis technique that arises in the human factors literature [7]. The technique involves an experimenter video-taping a person being assisted during the task, and then transcribing and analyzing the video using a
“syndetic” modeling technique. The end-result is an Interaction Unit (IU) analysis that uncovers the states and goals of the task, the user’s cognitive abilities, and the user’s actions. The abilities are broken down into recalling what they are doing, recognizing necessary objects like the kettle, and perceiving affordances of the environment. This model of cognitive abilities is defined a priori by experts in the psychology of dementia, but generalizes across tasks. The IU analysis is augmented by a small set of parameters that give the rate at which a user gains or loses abilities over time, and the likelihoods they will take certain actions in situations with multiple possibilities. Further, a set of sensors is proposed for the environment to provide evidence about task and behavior elements in the IU analysis. A POMDP controller is then automatically compiled from the IU analysis and specification of sensors and actuators for each environment [8,11]. The complete set of specifications is stored in a relational database, and we use a probabilistic relational model to unite the database and POMDP [8]. The database has an intuitive graphical interface, where users can drag-and-drop images onto the canvas to model the environment, and use interactive form controls involving canvas objects to specify actions and goals of the task (Figure 2). The user’s cognitive abilities are computed based on a specified dementia profile, and the list of sensors pertaining to the task is generated automatically. The interface also contains an ontology of objects and their usages, which can be expanded and shared across users. Therefore, it serves as not only the presentation layer of the database, but rather an abstraction of the cumbersome specifications of data that would otherwise require manual entry.

Although POMDPs are intractable in theory, there have been many recent advances in their solution and usage. In particular, Monte-Carlo methods have proven to put solutions to extremely large POMDP models within reach, allowing POMDPs for domains with up to $10^{56}$ states to be effectively solved [9]. We expect that progress will continue in this direction and that the use of POMDP models will evolve into a general-purpose control mechanism. Our own research has shown how to build hierarchical POMDP models for the assistance domains, and how the hierarchies follow naturally from the task analysis technique [10].

Figure 2. Current user interface prototype in development.

In the long-term, we expect the POMDP controllers to learn from interactions with end users (i.e., persons requiring assistance) over time using reinforcement learning techniques, report problem areas (where the controller is unable to help), and receive further instruction from humans (i.e., caregivers or other persons responsible for setting up the system). Reporting may also drive technological development, feeding a “marketplace” of assistive technology sensors
and actuators, thus creating an economic incentive for further development and engagement.

**Conclusions and Future Work**

From the user side, we are working to translate the needs expressed by caregivers [3] into the next “caregiver interface” design iteration for evaluation with new participants. Another focus is on developing a method to elicit comprehensive knowledge about users, home environments, and routines to guide and inform caregiver interface design. From the technology side, our current prototype is shown in Figure 2 and we show our proposed concept for an interface in Figure 1 and using a video demonstration at [6]. In both streams of research, we are aiming to build solutions that generalize across multiple users and applications. We are first uncovering the language through which a specific user (or group of users) express and specify smart home needs, and then developing formal models to translate this language into specifications for POMDP-based systems. In this way, we can enable users to customize and interact with smart home systems without any understanding of POMDPs and the nuances of relational models, thus making DIY smart homes possible for the widest range of users.

**Acknowledgements**

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**References**


Content-Based Image Retrieval with Hierarchical Gaussian Process Bandits

Abstract
A content-based image retrieval system based on relevance feedback is proposed. The system relies on an interactive search paradigm where at each round a user is presented with \( k \) images and selects the one closest to her ideal target. The approach based on hierarchical Gaussian Process bandits is used to trade off exploration and exploitation. Experimental results show that the new approach compares favourably with previous work both in efficiency and computational complexity and thus is highly applicable to online image retrieval systems.

Author Keywords
Content-Based Image Retrieval; Relevance Feedback; Gaussian Process Bandits; Self-Organizing Map

ACM Classification Keywords
H.3.3 [Information Search and Retrieval]: Relevance feedback.

Introduction
We consider the problem of content-based image retrieval (CBIR) in the case where images under consideration are not associated with any metadata such as keywords or tags. In such a situation, the user is unable to query the image database easily and so the system must extract the information regarding his or her need or search target.
through the limited feedback it receives from the user. For instance, imagine a journalist looking for an illustration to his or her article about maternity in the database of unannotated photos. The idea of a suitable image is very vague and the only opportunity for the journalist to navigate through the database is to give relevance feedback to the images proposed by the system. The system operates through a sequence of rounds, when a set of \( k \) images is displayed and the user must indicate which one is the closest to their ideal target image.

While this problem has been studied before (e.g. [2]), we propose a novel approach based on a 2-level hierarchical Gaussian Process bandits. We developed a protocol for choosing multiple arms at each iteration by utilizing past user feedback. First, we select a cluster containing the most promising set of images and at the next stage we select an image from that cluster to present to the user. We show that hierarchical approach is more efficient in terms of time complexity than its competitors and thus more applicable to on-line retrieval systems.

Many traditional image retrieval systems, such as Google Image Search, utilize image metadata, such as captions and tags. However, it is not always possible to tag new images quickly and efficiently. To resolve these issues a lot of work has been done recently in an attempt to incorporate the user feedback into the search (e.g. PinView [2]). However, systems of this kind often face problems with the usability due to the running time of each iteration of the algorithm and do not scale to large sets of images. In order to tackle these problems, we employ hierarchical Gaussian Process (GP) bandits [5], where Self-Organizing Maps (SOM) [4] of image features are used as layers in the bandit hierarchy. We call our algorithm GP-SOM.

The GP-SOM Algorithm

Self-Organizing Map

In order to save computation time in the on-line retrieval system, we precompute the Self-Organizing Map (SOM) of images. SOM is an unsupervised method for reducing dimensionality of input space by constructing an artificial neural network of instances that reflects their topological order. SOM provides the so-called model vectors that are treated in our algorithm as discretization of the input space. The preprocessing step results in an objects hierarchy which serves as an input to the hierarchical GP bandits algorithm.

Gaussian Process Bandits Upper Confidence Bound

The policy used for balancing exploration-exploitation is Gaussian Process Bandits Upper Confidence Bound (GP-UCB) [6]. At each iteration \( i \), we choose the best image to present to the user as \( \arg\max \{ \mu_i + \sqrt{\beta \cdot \sigma_i} \} \), where \( \mu_i \) is a predicted mean of the relevance score, \( \sigma_i \) is a standard deviation and \( \beta \) is a constant or some function of time to adjust the confidence level. In GP-UCB, we determine predicted mean as \( \mu = K_\ast K^{-1} r \), and variance as \( K_{\ast\ast} - K_\ast K^{-1} K_{\ast\ast}^T \), where \( r \) is the relevance feedback, and \( K, K_\ast \) and \( K_{\ast\ast} \) are parts of kernel matrix. \( K \) correspond to pairwise kernel function between all shown datapoints, \( K_\ast \) – between shown datapoints and those we have to predict, and \( K_{\ast\ast} \) – between images to predict [5].

Hierarchical GP UCB Bandits

We apply a 2-layer bandit settings: first we select a model vector and then an image that is sampled from images associated with a particular model vector. Thus, in the first layer, the arms are considered to be model vectors and we select one model vector. In the next step, arms are images associated with the chosen model vector and we select one image. At each level of the hierarchy, we apply
the GP-UCB algorithm. We repeat the selection procedure \( k \) times in order to obtain \( k \) images to present to the user.

**Analysis and Experimental Results**

We compare GP-SOM to two well-known exploration/exploitation algorithms – LinRel [1], which forms an integral part of the PinView system, and the GP bandit algorithm [5]. These algorithms were chosen because they rely on the same kind of feedback and object representation as the one we are developing.

Usually the weak point of exploration/exploitation algorithms is in their scalability and time-efficiency. The proposed approach tackles this issue in an effective manner and Table 1 summarises the complexity of the three algorithms we consider.

<table>
<thead>
<tr>
<th>Alg</th>
<th>( O(N^3) )</th>
<th>( O(N^{3/2}k^2) )</th>
<th>( O(N^{3/2}k^3) )</th>
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<tbody>
<tr>
<td>LR</td>
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<td>GP</td>
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<tr>
<td>GP-SOM</td>
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</table>

Table 1: Time complexity of the on-line part of LinRel (LR), Gaussian Process Bandits (GP) and Gaussian Process Bandits with Self-Organising Map (GP-SOM). \( N \) indicates the number of images in the dataset, \( i \) is the number of iterations and \( k \) is the number of images displayed at each iteration.

We also ran a set of simulation experiments to compare the performance of the algorithms. We used the MIRFLICKR-25000 dataset [3] consisting of 25000 images containing 3 sets of visual descriptors – texture, shape and color. All the reported results are averaged over 100 searches for randomly selected target images from the dataset. Table 2 presents the average number of iterations to find the target image for different values of \( k \).

<table>
<thead>
<tr>
<th>Alg</th>
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<th>10</th>
<th>20</th>
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<tbody>
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<td>25.6</td>
<td>16.2</td>
<td>8.9</td>
</tr>
<tr>
<td>GP</td>
<td>24</td>
<td>15</td>
<td>11.2</td>
</tr>
<tr>
<td>GP-SOM</td>
<td>13.3</td>
<td>12</td>
<td>8.7</td>
</tr>
</tbody>
</table>

Table 2: Comparison of the performance of LinRel, GP bandits and GP-SOM.

GP-SOM outperforms LinRel and GP bandits by at least 45% for smaller values of \( k \). For large values of \( k \), there is almost no difference between LinRel and GP-SOM, however GP-SOM is more computationally efficient than LinRel, i.e. LinRel is much slower and does not scale up to large datasets of images.

**Summary**

We propose a new content-based image retrieval system that trades of exploration and exploitation and is based on hierarchical Gaussian Process Bandits with Self-Organising Maps. The proposed approach is more computationally efficient than similar algorithms employing exploration/exploitation, such as LinRel and simple GP bandits. The initial experimental results also show that GP-SOM outperforms these two approaches. The next step in the development of our system is building a user interface and run extensive user studies to tune the parameters in the GP-SOM algorithm.

**Acknowledgements**

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References
Designing GUI for Human Active Learning in Constrained Clustering

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Abstract
In this paper, a novel GUI for human active learning in constrained clustering is described. Clustering is the most popular data mining technology, and in particular, interactive constrained clustering that uses constraints from a human is promising for practical applications. We propose a GUI that can expose the effects of given constraints by emphasizing them at the clustered results and provide multiple viewpoints that a user can flexibly change to derive human active learning. We fully implemented an interactive constrained clustering system with the GUI as a web service. We also conducted an evaluation experiment on image clustering with participants, and obtained results to support the effectiveness of our approach.

Introduction
Clustering is the most popular data mining technology, and in particular, interactive constrained clustering that uses constraints from a user is promising for practical application. In interactive constrained clustering, a user plays the role of a teacher to a constrained clustering system [2] and gives must/cannot-links as constraints. In such a situation, a user tries to select effective constraints and this human ability is called human active learning [4]. Furthermore, because a user’s cognitive load necessary to give constraints is well known to be significantly restricted...
and the maximum number of pairwise constraints was about 50 in our experiment, we needed to prepare a mechanism to support human active learning. Thus we propose a GUI that can derive human active learning. The GUI has two characteristics, exposing the effects of the last constraint given from a user and providing multi viewpoints with which a user can easily find an effective data-pair as a constraint.

Some constraints are not effective [6] in constrained clustering, and the cognitive load necessary for a user to give constraints is high in interactive clustering, thus we need to provide a mechanism in which a user can easily select only effective constraints for an interactive constrained clustering system. Since the constraints are considered to be training data for classification learning, traditional computational active learning like uncertainty sampling [11] and query by committee [13] might be useful in non-interactive constrained clustering. For interactive constrained clustering, we should use human active learning [4].

As far as we know, popular data mining tools that include Weka [9] do not provide an environment for interactive constrained clustering and a suitable GUI for human active learning. Interactive machine learning systems are closely related to this work. Such systems provide a user interface that supports a user in giving training data to the systems. Fails et al. originally proposed an interactive machine learning framework that supports the interactive training of pixel classifiers with a user for image segmentation [7]. CueFlik [8] also provided an end-user machine learning environment in which users can easily create rules for re-ranking images according to their visual characteristics. It was implemented for web image searches. CuteT [1] was designed to use interactive machine learning that learns from triaging decisions made by operators in a dynamic environment. It also had visualizations to support operators to quickly and accurately triage alarms. These interactive machine learning systems basically dealt with training data for classification learning, not constraints for constrained clustering, and explicitly did not provide an interaction design for deriving human active learning.

**Designing a GUI for human active learning**

We made an interactive constrained clustering system with a GUI that can derive human active learning, and investigated its effectiveness in performing clustering. The interactive constrained clustering system was implemented on a web server by using MATLAB, Perl, and JavaScript, and could run on a web browser. Figure 1 shows a snapshot of the interactive constrained clustering system’s UI. The system had the following special functions for human active learning.

![Figure 1: GUI for human active learning.](image-url)
• Exposing the effects of given constraints: The interactive constrained clustering system can expose data influenced by the last given constraint. We expect this function to make a user recognize the effects caused by his/her given constraint and to derive human active learning. The influenced data are identified by checking the change of a cluster to which data belonged after every clustering, and are emphasized by being circled like in Figure 2.

• Multiple viewpoints for the results of clustering: The interactive constrained clustering system enables a user to change viewpoints to see the distribution of data. We used multi-dimensional scaling [3] to show data in the 2D coordination, and provided multiple viewpoints by preparing pairs of eigenvalues as a 2D-coordination. In Figure 3, which shows 1(e), a user can freely select a viewpoint by mouse clicking, and the data distribution with the selected viewpoint is updated as in Figure 1(a).

COP-Kmeans [14] was used in our interactive constrained clustering system as a constrained clustering algorithm. Another approach to constrained clustering is metric/distance learning [10]. However, since it costs much because it needs complicated optimization and the response is sufficiently quick, we did not use it. The user gives only must-links. The user selects a pair of data for a must-link by using a main window (a), a magnifying window (b) and a selected data pair window (c), as shown in Figure 1. After the user determines a must-link in (d), the constrained clustering run and the data in (a) are updated. This procedure is repeated.

Experiment
We conducted a within-subject experiment with 16 participants (12 males, 4 females, ages 18~52). Two conditions, a proposed GUI (p-GUI) and a traditional GUI without the two functions (t-GUI), were prepared, and their ordering was counterbalanced. In each trial, a participant was asked to give 50 constraints one by one. The data were image files generated from CALTECH 256 by using bag of features [5] with SIFT [12]. A data set of three clusters comprised of “motorcycles”, “laptop PCs” and “starfishes” was prepared, and each cluster had about 50 pieces of image data.

We measured the number of constraints (must-links) necessary to achieve normalized mutual information (NMI) = 1.0 and the maximum NMI for 50 constraints as an evaluation. The average number of constraints (the upper limit = 50) for the p-GUI and t-GUI was 35.9 (SD = 10.6) and 46.1 (SD = 10.3), and the average maximum NMI was .97 (SD = .08) and .84 (SD = .13). These results are shown in Figures 4 and 5. We applied a t-test to them and found significant differences between the two levels in both evaluations (p = .007, .006). These results supported the effectiveness of our proposed GUI.

We also found that this human active learning

![Figure 2: Exposing the effects of a given constraint.](image2)

![Figure 3: Multiple-views selection (Figure 1(e)).](image3)

![Figure 4: Number of constraints to NMI = 1.0.](image4)
Conclusion
We proposed a novel GUI for human active learning in interactive constrained clustering. The GUI can expose the effects of the last given constraint to a user so that he/she can easily recognize the causality between constraints and clustering, and it can provide multiple viewpoints so that a user can quickly find effective data pairs as constraints. We conducted experiments with image clustering by using popular data sets to evaluate our proposed GUI. We experimentally compared the proposed GUI with a conventional system without the GUI, and obtained results to support the advantages of our proposed GUI.

References
Information Retrieval Perspective to Interactive Data Visualization

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Abstract
Data visualization has recently been formulated as an information retrieval task with a well-defined cost function; the display is optimized for a tradeoff between false positives and misses of similarity relationships which are defined by a metric in the input space. We extend the approach to cases when the metric is unknown and the similarities must come from the user. We introduce an interactive visualization method; the user points out misses and false positives on the display, the metric is gradually learned from the feedback, and the display converges to showing similarities relevant to the user.

Author Keywords
Interactive visualizer, nonlinear mapping, metric learning

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

Introduction
Exploration is crucial in data analysis when strong hypotheses are not yet available. Visualizations like scatter plots help exploration, and “looking at the data” helps form hypotheses to be tested later. What is relevant in data is usually not known a priori. We consider the setup where the user has some tacit knowledge about
similarity relationships in the data. Interactive visualization should then be used to let the user give feedback about what is relevant.

What data aspects are relevant can be encoded by defining the metric so distance between data depends on relevant aspects; most manifold learning methods use known distances. A recent method [1] formalizes visualization as an information retrieval task where the user retrieves neighborhood relationships from the display; in that work desired neighborhoods are assumed known. We now extend it to an interactive method where the metric is learned from user feedback. Unlike previous works our interactive process is optimized for a rigorous information retrieval user task: the metric and arrangement are iteratively optimized for a task of retrieving the analyst’s desired neighborhood relationships. In each iteration the user indicates “are neighbors”, “are not neighbors” for point pairs. We improve the visualization in two ways: 1. We iteratively learn a distance metric based on the feedback. 2. At each iteration we optimize the data arrangement to compress the learned neighborhoods onto the low-dimensional display. Our method combines the Neighbor Retrieval Visualizer (NeRV; [1]) with distance metric learning [2]; our method can be shown to minimize an expected information retrieval cost, expectation over the posterior of the metric inferred from user feedback.

**Information retrieval based visualization**

Let \( \{x_i\}_{i=1}^N \) be a set of input data samples. Let each sample \( i \) have an unobserved desired neighborhood \( p_i \), which in general is a distribution telling for each neighbor \( j \) the probability \( p_{ij} \) that \( j \) is a relevant neighbor to \( i \). The desired neighborhoods will be learned from feedback. The goal is to create output coordinates \( \{y_i\}_{i=1}^N \) for the data suitable for visual neighbor retrieval. On the display an output neighborhood \( q_i \) can be defined around each sample as probabilities

\[
q_{ji} = \frac{\exp(-\|y_i - y_j\|^2/\sigma_i^2)}{\sum_{k \neq i} \exp(-\|y_i - y_k\|^2/\sigma_i^2)}
\]

where \( \| \cdot \|^2 \) is squared Euclidean distance on the display; \( q_{ji} \) is the probability that an analyst starting from a central point \( i \) picks neighbor \( j \) for inspection. This simple mathematical form can be replaced by more advanced user models if available.

All properties of high-dimensional data cannot be represented on a low-dimensional scatter plot. Two kinds of errors will happen: misses are desired neighbors of a point \( i \) (high \( p_{ji} \)) that are not neighbors on the display (low \( q_{ji} \)). False neighbors are neighbors on the display (high \( q_{ji} \)) that are not desired neighbors (low \( p_{ji} \)). Misses and false neighbors can have a different cost to the analyst. The display should be optimized to minimize the total cost of errors.

It has been shown [1] that the total cost of misses corresponds to the information retrieval measure recall, and the total cost of false neighbors corresponds to precision. The measures have been generalized to divergences between probabilistic neighborhoods [1]: the Kullback-Leibler divergence \( D(p_i, q_i) = \sum_{j \neq i} p_{ji} \log \frac{p_{ji}}{q_{ji}} \) is a generalization of 1 − recall and \( D(q_i, p_i) = \sum_{j \neq i} q_{ji} \log \frac{q_{ji}}{p_{ji}} \) is a generalization of 1 − precision. The total information retrieval cost \( C_{\text{NeRV}} \) of misses and false neighbors in the visualization then becomes

\[
C_{\text{NeRV}} = \lambda E_i[D(p_i, q_i)] + (1 - \lambda) E_i[D(q_i, p_i)]
\]
where $E_i$ denotes expectation over the query points $i$. The parameter $\lambda$ in (2) controls the precision-recall tradeoff desired by the analyst: whether misses or false neighbors are more important to avoid. In experiments we choose to emphasize precision ($\lambda$ near 0) since then intermediate plots have a good local arrangement with few false neighbors; this could make it easier to browse data on the display as the analyst is not distracted by false neighbors.

If the desired neighborhoods $p_i = \{p_{ji}\}$ for each data point $i$ are known, all that remains is to optimize (2) with respect to the output coordinates $y_i$ that define the output neighborhoods $q_{ji}$. This can be done by gradient methods, see [1]. We treat the more difficult case when the desired neighborhoods are unknown; we next tell how to extend the approach to unknown desired neighborhoods.

**Interactive Visualizer Optimized for Information Retrieval Under Uncertainty**

The value of $C_{NeRV}$ in (2) can be computed only if the true desired neighborhoods $p_{ji}$ are known (in contrast, the retrieval neighborhoods $q_{ji}$ can be computed as simple functions of output coordinates $y_j$). When the underlying desired neighborhoods are unknown, but evidence of the desired neighborhoods is available in the form of user feedback, the rigorous approach is to treat the desired neighborhoods as missing values, and optimize the expectation of the cost function over the missing values. That is, we optimize the visualization for information retrieval under uncertainty. This is written as

$$E[C_{NeRV}] = E_{\{p_i\}\mid F}[\lambda E_i[D(p_i, q_i)] + (1 - \lambda)E_i[D(q_i, p_i)]]$$

where $E_{\{p_i\}\mid F}$ denotes expectation over the possibilities for different true desired neighborhood distributions $\{p_i\}$; the expectation is taken over a posterior distribution of the possible neighborhood distributions, conditional to the evidence from feedback $F$.

Assume that the desired probability of data point $j$ (with features $x_j$) being selected as neighbor of $i$ follows a Gaussian falloff in an unknown metric with metric matrix $A$: $p_{ji} = \frac{\exp(-||x_i - x_j||_A^2/\sigma_i^2)}{\sum_{k \neq j} \exp(-||x_i - x_k||_A^2/\sigma_i^2)}$, where $\sigma_i$ specifies the width of the Gaussian and $||x_i - x_j||_A^2 = (x_i - x_j)^T A (x_i - x_j)$. Neighborhoods $q_{ji}$ on the display simply use Euclidean falloff for output coordinates $y_j$ (Eq. (1)). The expectation over possible desired neighborhoods in (3) then reduces to an expectation over the metrics, so that

$$E[C_{NeRV}] = E_{A\mid F} [\lambda E_i[D(p_i, q_i)] + (1 - \lambda)E_i[D(q_i, p_i)]]$$

where the desired neighborhoods $p_i$ are now functions of the metric matrix $A$, and $E_{A\mid F}$ denotes expectation over a posterior distribution of metrics $A$ given the feedback $F$. We use a simple way to approximate the expectation by taking the value at a posterior mode of $A$.

The optimization goes as follows: At each iteration, learn a variational approximation to the posterior $p(A\mid F)$ for the metric from feedback as in [2], then optimize the output coordinates to minimize expected Kullback-Leibler divergences of neighborhoods:

$$E_{A\mid F} [\lambda E_i[D(p_i, q_i)] + (1 - \lambda)E_i[D(q_i, p_i)]]$$

where the expectation is approximated by taking the value at the mean of the variational posterior approximation. As in the previous section, $D(p_i, q_i)$ generalizes 1 − recall (proportion of misses when retrieving neighbors in $p_i$ from the display using $q_i$) and $D(q_i, p_i)$ generalizes 1 − precision (proportion of false neighbors in $q_i$), and $\lambda$ controls the tradeoff between optimizing precision vs. recall, but here these quantities are optimized as expectation under uncertainty about the user’s choices.
Experiments and Conclusions
In experiments the user picks pairs of data points and indicates their relationship as a false positive or a miss. Data sets: articles published by Helsinki Institute for Information Technology HIIT researchers; part of DARPA TIMIT phoneme data; similar results with Wine from UCI machine learning repository (figures omitted). Each data set has additional noise features, assumed not beneficial for retrieving desired neighborhood relationships.

We evaluate our method in three ways: 1. we evaluate the benefit of utilizing a visualization in finding good feedback pairs, 2. we test whether the iterative interaction and metric learning help the user task of visual neighbor retrieval, and 3. we present a small case study with a real user. In experiments 1 & 2 each iteration yields 3 pairs of feedback by an artificial mechanism: we compare the current visualization to known desired neighborhoods and give the worst misses or false neighbors as feedback.

Fig. 1 shows that using the visualization to pick feedback pairs improves metric learning compared to picking the pair randomly, and that our information retrieval approach outperforms traditional multidimensional scaling (MDS) coupled to metric learning. Fig. 1 also shows that the visualizations improve in retrieving desired neighborhoods as feedback is given. Fig. 2 shows a user study using scientific articles as the data set. The user goal was to arrange the scatter plot in such a way that similar articles from the user’s perspective are also close to each other on the screen by giving pairwise feedback. To help browsing, when the user hovers the mouse over a point we show the title, year, and authors of that paper. Points given as feedback were also indicated by a coloring. Fig. 2 shows that as feedback was given, the metric improves and articles become arranged by their broad research fields.

In conclusion, we introduced an interactive visualizer which organizes data according to users’ feedback on similarity. It learns metrics better than non-visual online metric learning, and shows neighbors better than a simple distance preservation approach.

Figure 1: Left: using the visualization to choose feedback pairs (“Vis”) improves iterative metric learning compared to selecting pairs randomly (“Random”); we show the portion of weight remaining in unimportant features. Right: our information retrieval based visualization (“NeRV”) shows desired neighborhoods better than using metric learning with traditional MDS. We show evolution of the area under the precision-recall-curve of retrieving user’s ground truth neighborhood. Results are shown with TIMIT data.

Figure 2: User experiment. Points are scientific articles, colors (not shown to user) are their research fields: green=machine learning, red=complexity theory, black=human-computer interaction and blue=social psychology. As iterations proceed, the metric is learned from feedback and the display becomes arranged by the hidden colors.

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References
Interactive Analytics for Industrial Systems

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Abstract
We present a case for a unified interactive analytics framework for large scale industrial systems and discuss opportunities and challenges in developing such a framework. We also present an instantiation of such a framework for a large smart-grid utility.

Author Keywords
Industrial Data, Interactive Analytics

ACM Classification Keywords
H.5.m [Information interfaces and presentation (e.g., HCI)]: Miscellaneous.

General Terms
Framework, Industrial Internet

Introduction
Industrial data and system-automation pose unique analytics and presentation challenges. While approaches have matured to some extent in analyzing large scale social media type data, huge challenges await when it comes to analyzing and interpreting industrial data from systems such as aircraft manufacturing and servicing, turbine maintenance for energy, analyzing usage and behavior patterns of industrial devices, connecting data from multiple devices and so on. Industrial systems are
extremely complex and incorporating analytics to draw insights pose unique challenges:

- analyzing transient data from sensors that is not just temporal but also changes over time
- dealing with extremely expensive labeling processes
- fitting reporting and collaboration to workflows
- maintaining security and satisfying regulatory requirements while supporting distributed user tasks
- dealing with multi-modal data
- dealing with decentralized and distributed data
- connecting analyses from different aspects (data chunks, data modalities, perspectives, geographic locations, etc.).

The fact that human intervention is not just desired but required in many cases necessitates a unified framework that naturally lends itself to an interactive setting. This enables integrating the expert not just in the labeling process (as in the conventional machine-learning sense) but also at other stages notably, data quality and validation, knowledge capture allowing for information organization and more efficient analyses of data in an industrial systems setting.

**Interactive Framework**

Figure 1 presents an map of interactive analytics framework that shows various stages where human expert(s) can be integrated in the analytics pipeline as well as how different learning approaches fit in the pipeline.

![Figure 1: An interactive analytics framework. The grey components represents analytics layers while the black boxes represent the user interaction layer with bidirectional arrows representing information flow to and from both components.](image)

Note how the user can interact right from the data ingestion layer (with inputs to aspects such as data scrubbing, formatting, etc.) all the way to the reporting layer. In industrial settings an expert’s input can be instrumental in data quality. For instance, based on usage patterns, an expert can quickly validate sensor data from wind turbines. Similarly, in the learning steps, an experts can not only be useful in annotation or labeling but also in validating labels and enhancing knowledge base (e.g. by incorporating domain knowledge on diagnostics or anomaly detection for an industrial component/device).

Machine learning approaches such as active learning and reinforcement learning with user inputs are subsumed in
the learning abstraction layer that actively use the expert
to obtain labeled samples in incremental learning steps.
Examples of such approaches deployed in commercial
setting exist[3]. Note that the user interaction
components are not limited to one or a few users. These
can naturally include wider participation (e.g.
crowdsourcing for labeling and learning models). As [2]
points out: “the key to human interaction with big data
will be metadata”. Involving experts to help build these
knowledgebases of metadata (through the knowledge
capture step in Fig 1) will be instrumental in the Big Data
scenarios that are reality in any practical application and
deployment of analytics. Advances in healthcare have, for
instance, come up with such taxonomies as SNOMED,
RxNorm, and so on [1] that allows for an organized view
of data and analyses. Further, integrating other
approaches to communicate the analyses, results and even
data in current Big Data case pose its own set of
challenges. Approaches that allow for effective
communication, such as storytelling with value-add
metadata [2], big data visualization and interactive
crowdsourcing [4] will be a significant piece to incorporate
in addition to intelligent user interfaces.

Below, we discuss an instantiation of such framework that
we undertook for a large utility.

Instantiation
Utilities are complex systems, and it takes collaboration to
ensure a smart grid is functioning correctly. Utilities have
operations centers where engineers ensure proper
functioning of the grid, and attempt to predict potential
problems and mitigation strategies. When a problem
appears, engineers often work with technicians in the field
to resolve them. Utilities in northern states and in Canada
is face major problems in storm seasons as a result of
fallen trees and branches on power lines. Cutting
vegetation potentially dangerous for power lines is both
expensive financially (costs ranging in hundreds of millions
of dollars) and environmentally.

We created an application for one of these utilities that
enabled them to localize the areas where problems were
likely to occur ahead of time so they could focus their
efforts more efficiently; and as weather that was likely to
impact the grid approached, it let them deploy their crews
in these areas. While machine learning algorithms play a
key role in accomplishing this prediction, an important and
indispensable part of the solution is the user interaction
component. The presentation environment is a set of
large screens tied together to provide an overview of an
entire region letting engineers dive into the complex set of
variables represented in the data. Several new interaction
models are being tested that further allow groups of
engineers to collaborate while exploring the data.

To build the application, we began by leveraging 5 years
of growth data from satellite imagery. We represented
that data overlaid on satellite imagery of the geographic
region covered by the utility, and enabled the engineers to
view changes in the vegetation over time as well as project
future growth. The engineers can also visualize their
power grid overlaid on the geography and pull up a view
of past outages. Analytics applied to past vegetation
growth and (possibly associated) outages under various
conditions gives the engineers the ability to focus on areas
marked as the most probable candidates for potential
outages. These projections allow for scheduling preventive
pruning of the vegetation most efficiently. The weather
data can also be overlaid on the combined visualization
allowing for a temporal ordering. As weather moves in
engineers can focus on areas that are likely to be hit first.
Further, they can see problems that are occurring and have an initial diagnosis of the root causes of the problems. Consequently, they can take specific actions to restore power and minimize damage.

Extensions of this solution currently underway will allow engineers to mine the data to see the variables that correlate most highly with problems as they occur, and to explore how combinations of those variables make various problems more or less likely. The resulting predictions of high probability problem areas can be overlaid on the map, and the engineers can pull up very detailed street views of the target areas. These views and guidance on what actions need to be taken can then be passed on to technicians in the field who can collaborate with the engineers in the operations center as they prevent, troubleshoot, or fix problems they encounter. The engineers in the operations center, with their very large screen collaborative visualization environment have the ability to view context that the individual engineer otherwise doesn’t have. Hence, they can provide that context, the results of visualization and modeling, and other information to the field to enable the field force to be more effective.

Summary
Interactive analytics framework allows for incorporating users (domain-experts) in the learning-feedback loop, enabling knowledge and expertise capturing, system enhancement and information accumulation, more efficient communication and reporting, and connecting multiple knowledge and information sources. This further enables an evolving and integrated set of tools that empower users to utilize and improve results of the analytics. Developing such a unified framework will be a significant step forward in making data and insights and importantly analytics approaches not only accessible but also adaptable based on broader human understanding.

References
Interactive Learning of Plays for Bio-Inspired Robots with Body Undulation

Figure 1: An illustration of gait motion for snake-inspired robots. It is quite difficult to find optimal time-varying functions for the joint positions, even for simple motions such as the one shown here.

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Introduction
Several natural creatures — e.g., snakes, caterpillars, lampreys, eels, etc. — do locomotion via body undulation. Many research groups are developing robots that move in the same way [4],[2],[3]. To locomote using body undulation, robots need gaits. A gait is a pattern of joint movements in which the joint parameters usually have the same starting and ending values, so that the gait can be used repeated (Figure 1). A gait can be viewed as a set of continuous functions that describe how the joint values change as a function of the time. The dependencies among the joint variables that induce a continuous periodic motion for a robot are usually described in terms of the primitive elements (i.e., sub-gaits) and relationships among those elements. But for body-undulation robots, it is not well understood what should be used for these primitive elements. This paper summarizes our ongoing work on interactive learning gaits for snake-inspired robots and and thoughts about how human teaching and demonstrations may help the computational learning algorithms.

Background and Preliminaries
Our goal behind our first experiments with learning gaits for snake movements was to use Artificial Intelligence techniques to discover these primitives by controlled experimentation. We developed a formalism and a
learning algorithm, based on Self-Organizing Maps (SOMs) [5], that made successive local modifications to the configuration parameters, such as joint angles, joint phase times, and others. We then used simulation results to analyze how sensitive the snake’s behavior is to the parameter changes. As the search progresses and more data is analyzed, our hypothesis was that this approach would enable the algorithms to make more informed local modifications.

Being a fully automated one, this approach did not work very well in our preliminary experiments. There are several observations related to the reasons why: (1) the snake models we used in our simulations included more than 10 joints, which created a high-dimensional continuous space to be learned; (2) it was very difficult to coordinate learning of different joints independently, as was in our approach. We observed that the front of the snake and the back of the snake moved in different directions using the learned knowledge in the simulations; and (3) the real-world physics posed a challenge for the learning algorithm. The algorithm could not capture by itself the frictional forces that were active on the joints.

To alleviate these issues, we are currently developing a new approach based on interactive learning of gaits. While there have been several “learning by demonstration” approaches developed for learning primitive plans as well as high-level behaviors for robots (see [1] for an excellent survey), most of these are classification or regression based techniques developed to produce a mapping from the states of the world to the actions of the robot. Instead, we plan to use our Playbook® control system [7] for interactive gait learning. Playbook® is based on the concept of “supervisory control” [9], where operators select tasks for automation and provide instructions for how to perform them, though there may be many variations as to how this is accomplished. The key to supervisory interaction is a shared understanding of objectives and methods of achievement by both supervisor and subordinates. This is necessary so that the snake behaves in ways that adhere to the operators intent, and so that its actions are predictable. While none of the subsequent techniques described below has yet been applied to the problem of body undulation, we believe they hold promise to overcome the shortcomings of our automated learning approach.

Exploiting Human Guidance and Teaching

A playbook is one way of achieving supervisory control. Furthermore, it is a particularly efficient method of controlling complex behaviors, particularly involving multiple, heterogeneous agents, all by means of a simple command. Playbooks can also provide increased levels of flexibility if their plays can be augmented by a means of refining, tuning or discussing with the play framework as a starting point. It is much easier, for example, for a supervisor/coach to say “We’re going to do an End Sweep Right, but this time, I want the wide receiver to fake left” than to define a new suite of actions from scratch.

The low and intermediate level tasks which Playbook® reasons about can be assembled into novel plays, though this is currently a process of moving chunks of software code around, adapting them when necessary and integrating them. We have long envisioned a UI in which graphical elements stand for such low level tasks/behaviors as well as the code which enables them. Then creating a novel play could be as easy as grabbing graphical pieces of the types desired and, literally, assembling them to form the new desired play behavior.

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1Playbook® is a registered trademark of SIFT, LLC.
In fact, there is no reason in principle that such “building blocks” could not be shaped and color-encoded to illustrate which pieces can be associated with which others — using the metaphor of a jigsaw puzzle or of “Tinker-Toy task modeling” to convey to users what behaviors logically follow or are required to enable which others. There are existence proofs that show that such graphical procedure constructors are viable, at least in small domains. One of the most successful such tools is the Lego Mindstorms robot programming language and GUI (Figure 2) designed to enable children aged 10+ to create reusable plans for robots they built using Legos kits.

![Figure 2: The Lego Mindstorms™ Graphical Programming Language illustrating a series of steps ending in a looping behavior (cf. www.mindstorms.lego.com).](image)

The benefits of graphical play construction approaches is that they should prove highly intuitive and usable for describing different strategies for snake movements, but the challenge will be providing the expressiveness required to create fully usable plays with the precision desired all in a manageable graphic vocabulary. One of the goals of the play construction process should be to exploit the discovered sub-gaits by the learning algorithms, the relationships among them, and the sub-gaits in order to define a vocabulary of snake behavior. Humans are very capable in identifying behavior patterns at high levels and we aim to take those patterns described for the parts of the snake robot, and extrapolate those sub-gaits for the other parts of the robot. It should be possible to achieve this goal by either by simply replicating the sub-gaits with the desired behavior to the rest of the joints, or by developing local-search methods to modify sub-gaits before we assign it to the other parts of the robot.

A gait constructed for a part of the robot will originally specify the joint and link operations for that part only. Thus, it’s necessary to generalize that gait specification to describe a joint behavior in order to generalize the gait to be used for the rest of the robot. To achieve this, we will need to produce generalizations, and in some cases, specializations of the equivalence classes and compositions of gaits. Our idea is to combine inductive and deductive logical inference techniques with analytic numeric methods in order to reason over continuous parameters in models of body undulation. The inference methods will use the relationships discovered among the sub-gaits relevant to a gait behavior. Based on the observations we obtain from the simulation of a gait sequence, we believe that this approach will produce high-level macro-gaits with conditions that specify the circumstances they should be applied. At each level of such hierarchy of macro-gaits, the conditions on the gaits will specify how to organize behavior patterns (or approximate such organizations) in order to achieve the given objectives.

In particular, we are developing a way to extract useful behavior patterns from the observations over the system’s
execution over time. Our previous work on Bayesian learning [6] suggests that it is possible to compute estimates of the bounds of these behavior patterns; i.e., the time a particular behavior starts to emerge, the time it fades out, and the changes in the component parameters of the system during that time. These bound estimates can then be used as definitive characteristics of potential equivalence classes of gaits. Then, if two gaits have similar starting and ending parameters and they both induce straight motion in the simulations, then an EBL-based algorithm [8] can hypothesize that executing those gaits one after another will also realize a straight motion. This will be useful if the snake robot is trying to achieve such motion in the world. Alternatively, if the objective is to optimize the speed of the robot while moving forward, we can analyze the angular velocities on the joints of these gaits and generate a new gait that is slower or faster than both by modifying the parameters, depending on the optimization criterion and the domain theory available.

Conclusions and Future Work
Our goal is not strictly to mimic the human teacher; instead, it is to computationally understand good configurations for the continuous parameters in models of body undulation to react to certain real-world situations, using the initial example as a model, and generalize those reactions to new situations which accomplish the same goal. Although we believe our first AI-based approach to this problem has not been very successful, demonstration based approaches have the advantage of leaving the user in charge of telling the system when and what to learn from, and are therefore somewhat less unpredictable than other learning approaches. In particular, supervisory delegation/control systems limit the discrepancies between the teacher and the learner (i.e., the snake). However, ambiguities can still exists in the human input; thus this remains an important future work that deserves further investigation. Another challenge we will further investigate is to develop a better computational models of how failures propagate and thus, prevent the failures biasing the learning and extrapolation of the gaits for the other parts of the snake.

References
Interactive User-Feedback for Sound Source Separation

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Abstract
Machine learning techniques used for single-channel sound source separation currently offer no mechanism for user-feedback to improve upon poor results and typically require isolated training data to perform separation. To overcome these issues, we present work that applies interactive machine learning principles to incorporate continual user-feedback into the source separation process. In particular, we allow end-users to annotate errors found in source separation estimates by painting on time-frequency displays of sound. We then employ a posterior regularization technique to make use of the annotations to obtain refined source separation estimates and repeat the process until satisfied. An initial prototype shows that the proposed method can significantly improve separation quality compared to previous work and facilitate separation without isolated training data.

Author Keywords
Sound, audio, source separation, user-feedback, interactive machine learning

ACM Classification Keywords
H.5.2 [User Interface]: User-centered design, interaction styles; H.5.5 [Sound and music computing]: Methodologies and techniques, signal analysis, synthesis, and processing; I.5.4 [Applications]: Signal processing

Figure 1: (First Row) Mixture spectrogram of Mary Had A Little Lamb. (Second Row) Initial poorly separated E notes (left) and remaining notes (right). (Third Row) Annotations overlaid indicating incorrectly separated regions. (Bottom) Refined output after user-feedback.

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⋆This work was performed while interning at Adobe Research.
Introduction

For many music- and audio-related tasks, it is desirable to decompose a single-channel recording of a mixture of sounds (e.g. pop song) into its respective sources (e.g. drums, guitar, vocal, etc.). Over the past decade, non-negative matrix factorization and related latent variable models have become common approaches for this purpose. While these methods can achieve high-quality separation, typically the results are less than ideal. Additionally, such methods offer no mechanism to improve upon poor results and are ineffective when no training data is available. To mitigate these issues, we first propose an interaction method to incorporate user-feedback into the separation process, and then extend a popular source separation technique to incorporate the feedback.

Interaction

To incorporate user-feedback into the separation process, we allow an end-user to initially separate a recording, listen to the separated outputs, paint on spectrogram displays\(^1\) of the output estimates, and re-run the process until satisfied, as shown Fig. 1 as a sequence of spectrograms and Fig. 2 in block-diagram form.

When painting on the display of a particular output sound, a user is asked to identify regions that are incorrectly separated. Opacity is used as a measure of strength and color is used to identify source. For simplicity, we focus on separating one sound from another, although the method can be used to separate more than two sources at once.

Methodology

To initially separate a given recording, we use probabilistic latent component analysis (PLCA) [2, 3]. PLCA is a time-varying mixture model that decomposes audio spectrogram data into a weighted combination of prototypical frequency components over time. The frequency components and weights for each source in a mixture are estimated using an expectation-maximization algorithm. These results are then used to estimate the proportion of each source in the mixture and subsequently reconstruct each source independently.

To incorporate the user-feedback described above, the painting annotations serve as penalty weights which are used to constrain our probabilistic model via the framework of posterior regularization (PR) [1]. PR allows for efficient time-frequency constraints that would be very difficult to achieve using prior-based regularization.

To test the proposed method, a prototype user-interface was developed and used to separate several real-world sound examples. Using standard evaluation metrics, we demonstrate that the method can achieve high-quality results, and even perform well with no training data (see https://ccrma.stanford.edu/~njb/research/iss/ for audio and video demonstrations). Such results show great promise for the use of interactive user-feedback for sound source separation.

References


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\(^1\)A spectrogram is an auditory display of sound which roughly depicts energy as a function of time (x-axis) and frequency (y-axis).
Abstract
Coactive Learning is a model of interaction between a machine learning system and a boundedly rational human user, with the common goal of providing results of maximum utility to the user. At each step, the system (e.g. search engine) receives a context (e.g. query) and predicts an object (e.g. ranking). In response, the user’s interaction with the system (e.g. clicks), provides a slightly improved – but not necessarily optimal – object as feedback. For this seemingly weak type of feedback we propose new learning algorithms which are efficient, robust, and surprisingly powerful, as shown from a theoretical and empirical standpoint.

Author Keywords
Online Learning; Structured Prediction

ACM Classification Keywords
I.2.6 [Artificial Intelligence]: Learning

Coactive Learning Model
A wide range of systems in use today, such as Search and Recommendation Engines, follow the same repeated interaction pattern between the user and the system: First the user issues a command (e.g. query), and the system presents a structured object (e.g. ranking) as the result. The user, in turn, interacts with this result, which provides
implicit feedback from which the system can derive an improved object (e.g., reordered ranking). However, unlike in the standard machine learning model where the optimal object is required as feedback, here the feedback typically provides only an incremental improvement over the presented result. For example, clicks on the web-search results \( B \) and \( D \) for the ranking \([A, B, C, D, ...]\), can help us infer that the user would have preferred the ranking \([B, D, A, C, ...]\). However, this is unlikely to be the best possible ranking. Thus the main challenge here is to learn from this weaker preference feedback in a robust manner.

**Feedback Model**

To theoretically characterize the performance of coactive learning algorithms, we proposed a number of different feedback conditions [2]. For example:

\[
U(Feedback) \geq U(Present) + \alpha(U(Opt) - U(Present))
\]

which simply says that the utility improvement of the feedback should be at least a constant fraction \( \alpha \) of what it would be if the optimal was provided. This conditions can be further relaxed to lead to more realistic feedback assumptions, as discussed in [2].

In human subjects experiments we verify that implicit feedback from clicks does indeed provide reliable preference feedback in web search [2]. The results are summarized in Figure 1, which shows that for only 10% of the queries the preference from implicit click feedback does not match explicit expert judgment.

**Learning Algorithms**

We propose several learning algorithms within this coactive learning framework (see [2, 1]). The simplest example is the Preference Perceptron shown as Algorithm 1, which makes a simple perceptron-style update using the weak preference feedback (instead of the optimal feedback, as done in the normal perceptron). Despite its simplicity, we can theoretically prove (and have confirmed empirically) that the algorithm has strong convergence guarantees. In particular, we can prove regret bounds showing that (a) as time goes on, the algorithm's performance keeps improving; and (b) the algorithm gracefully handles noisy and poor quality feedback. For more details, we refer you to the original papers.

**Further Extensions**

The generality of the framework, allows us to extend these techniques to different problem and application domains. For example, [1] uses coactive learning for the task of diversified retrieval/recommendation. Ongoing work includes extension to other applications that fall into this schema, ranging from news filtering to personal robotics.

**References**


Mixer: Learning Relational Web Extraction Interactively from a Crowd

Extended Abstract
The web provides access to a large quantity of relational data which users consult frequently for decisions in their personal and professional lives. Automated tools, however, generally cannot understand the relational data, making it nontrivial for users to carry out sophisticated analyses or actions using multiple parts of the data. Organizations that require such analyses typically fill the gap with human users. Previously, we have found [5] that administrative users spend a lot of time engaging in manual construction of structured spreadsheets from web relational data. Given a fixed target schema and lots of data, machine learning models can successfully extract tuples [4], but users encounter novel or idiosyncratic schemas and templates regularly in these tasks. We explore how the efforts of these end users engaged in these tasks can be combined into a crowd, whereby the efforts of crowd members directly lighten the load of other crowd members while simultaneously contributing to a growing pool of training data for comprehensive models.

Our approach incorporates end users’ embrace of spreadsheets for relational data [1,3,5] and asks the users to perform familiar actions within an instrumented environment. We attempt to strike a bargain with the user, whereby the user executes only a subset of the selection actions required. From these examples, our system applies programming by demonstration to extrapolate the rest of the table in real-time. The user can review and revise the examples until the table conforms to expectations. Thus the user extracts the table they wanted in the first place with less effort, leaving behind data the system can use to train models. As an added user benefit, if some other user has provided data about a given page, the user can simply download the current table with no interaction.

This approach presents several challenges in terms of both human factors and machine learning. Since our point of departure is that users without technical training typically perform these mundane web scraping

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tasks, we must ensure that the system is usable by end users without programming training. On the machine learning side, we examine which techniques supply high quality extrapolations while training and executing in time acceptable to a user in the loop. Additionally, we investigate the problem domain to determine which techniques generalize best from partial examples on disparate sites to complete scrapers for unseen sites.

We present the following contributions. We have gathered an evaluation corpus containing several hundred websites, which contain relational data indicated as interesting by workers on Mechanical Turk. We present a qualitative analysis of this corpus, with insights into how web developers empirically encode relational data for the web. We present a working software tool, which preliminary user studies indicate can be used by actual nonprogrammers to construct scrapers for webpages. Based on this tool, we derive an estimate for the number of web relations which would be accessible to automatic scraping. Through integration with the integration tool [2] which our previous work showed to be usable by nonprogrammers, this tool has great potential for allowing end users to automate web extraction tasks. Lastly, we compare machine learning techniques for extracting relational data from webpages. Specifically, we contrast different graphical models which assert different dependencies between the nodes of the webpage. We provide an empirical comparison of the models generated, with especial attention to which models best tradeoff accuracy versus responsive improvement for the user in the loop.

References

Figure 1. A screenshot of the tool, implemented as an extension to the Firefox browser. On the left is the webpage containing a relation (not necessarily using HTML table notation) and on the right is an example table the user constructs by dragging and dropping. When the user expresses satisfaction with first rows of the table, the system extrapolates the remaining rows and shows them to the user for review.
Accelerating Interactive Evolutionary Algorithms through User Modeling

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Abstract
Interactive Evolutionary Algorithms (IEAs) are a powerful explorative search technique that utilizes human input to make subjective decisions on potential problem solutions. But humans are slow and get bored and tired easily, limiting the usefulness of IEAs. To get around these problems we have developed a system which continuously builds a model of the user and uses this model to drive evolutionary search. Our system is called The Approximate User (TAU) and we have demonstrated it on a simple line-drawing task. In comparing the TAU IEA against a basic IEA it is found that TAU is 2.5 times faster and 15 times more reliable at producing near optimal results.

Author Keywords
Evolutionary Design, Interactive Evolutionary Algorithm, User Modeling

ACM Classification Keywords
I.2.6 [Artificial Intelligence]: Learning

Introduction
Interactive Evolutionary Algorithms (IEAs) are a powerful explorative search technique that utilizes human input to make subjective decisions on potential problem solutions. In traditional interactive evolution, a human user is
presented with one or more candidate individuals being evolved for selection. The human user directly performs selection and then the favored individuals are selected for propagation of offspring into the next generation. Reliance on human input has problems such as the people are many orders of magnitude slower than computers and the quality and accuracy of human input greatly degrades with repeated prompts for input [3]. To accelerate the search process we have developed an advanced IEA which uses user modeling as the means to accelerate search performance.

The system we have developed is called TAU, for The Approximate User. With TAU, each time the user indicates their preferences, this feedback is stored in a directed graph of their preferences. This relations graph of preferences is used to create a model of the user’s preferences and it is this user model which acts as the fitness function in the TAU-IEA [2, 1].

An example relations graph is shown in Figure 2(a) and contains six individuals (A through F). There are nine relations that can be derived from this graph – indicating the user’s preference from past queries – with the first five relations being the arrows that are shown. The rest are: A is better than E; A is better than F; C is better than E; and C is better than F. To continue growing the relations graph, each prompt to the user contains some individuals already in the graph, and some new individuals from the current population, Figure 2(b). Once the user has submitted their preference, this is used to update the relations graph, Figure 2(c). This updated relations graph – now with 21 relations – is then used to train an updated version of the user model which can correctly predict these preference relations.

For the work presented here we are using an ensemble of three ANNs to create a user model. Each ANN in the ensemble has a single hidden layer of 7 hidden units, a 40% connection density of the available, with weights randomly selected in the range of -0.1 to 0.1. Each ANN is trained using backpropagation for at most 50 iterations through the training data or until the training error is less than 0.001.

One concern with training classifiers is the size of the training set. In the above example, 4 candidates were presented to the user and, after just a couple of iterations, there were 21 relations. When more candidates are presented to the user the relations graph starts larger and grows even faster. For example, with 15 candidates shown and the user selecting 3 there will be 36 relations after 1 iterations. If again the user selects 3 out of 15 candidates
in the second iteration there will then be 108 relations in the graph. Thus the data to learn from grows quite quickly.

Once a good user-model is trained, it is used as the fitness function for a traditional Evolutionary Algorithm (EA). The EA then evolves candidate designs using a version of tournament selection to decide which individuals are the best. A tournament consists of comparing two candidate designs and using the user model to predict which one the user is most likely to prefer.

To test our approach we developed a simulated human user to drive the IEAs and tested them on a design problem of trying to create a square out of a connected sequence of four lines. An example of the application with a 3x5 grid of designs is shown in Figure 3. The left image (Figure 3(a)) shows an initial set of randomly generated line drawings and the right image (Figure 3(b)) shows the results after a few selection rounds using the TAU IEA.

For these experiments 100 trials were run with both the basic IEA and the TAU IEA. Experimental results show that search with TAU’s user modeling is about 15 times more reliable, achieving 98% of optimal solutions in 99% of its runs whereas the Basic IEA did this in only 6% of its runs. Also, the TAU IEA achieved near-optimal results about 2.5 times faster than the basic IEA.

In this work a human user was modeled by an ANN but other types of classifiers may work better. We expect that by developing better approaches to modeling a human user’s preferences that the TAU IEA can be made faster and able to scale to more difficult problems.

References
User Selection of Clusters and Classifiers in BBAC

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Abstract  
The Behavior-Based Access Control (BBAC) project seeks to address the increasingly sophisticated attacks and attempts to exfiltrate or corrupt critical sensitive information. BBAC uses statistical machine learning techniques (clustering and classification) to make predictions about the intent of actors establishing TCP connections and HTTP requests. Administrators will need to assign new computers to appropriate clusters, to be alerted about changes in cluster assignments, to select classifiers and settings to use, and to monitor accuracy of the system. We discuss the requirements and our current approach in this Interactive ML application domain.

Author Keywords  
Interactive, application domain, user, classifier, clustering

ACM Classification Keywords  
H.5.2 [Information interfaces and presentation (e.g., HCI)]: User-centered design.

Introduction  
Current cyber security monitoring systems have several shortcomings: they 1) have narrow focus and are signature-based, 2) use static policies, and 3) don’t use audit data for analysis until it is too late. This leaves systems vulnerable to sophisticated attacks including...
0-day and insider attacks. Behavior-Based Access Control (BBAC) [2] seeks to address these issues by performing analysis at multiple layers, including the network layer, application layer, and document layer. BBAC uses clustering to form groups of computers that have similar behavior. Classifiers are then trained for each cluster. Currently we are using both HTTP and TCP logs in our analyses. The techniques we use for HTTP data processing are similar to those used by Ma et al. [1] to detach malicious URLs. Our architecture is based on a cloud framework that will allow the clustering and classifiers to be trained at least once a day and will allow rapid classification of computer behavior.

User Interaction

The users for BBAC will be system administrators interacting with both the training side of the system as well as the real-time monitoring part of the system.

During the training phase, the system will re-analyze the clusters and build new classifiers. Changes in clustering might trigger user notifications as well as changes in classifier performance. Our system will compare its performance using newly trained classifiers against the previous baseline and note changes in behavior. Depending on operating conditions, different latency, and true positive and false positive rates may be desired. As system administrators are unlikely to be experts in machine learning, a key question we will need to answer is how to best present the accuracy of the re-trained classifiers. Additionally, our system will train multiple classifiers with different settings. A second key question is what data should be provided to enable the user to select a classifier.

New computers will be added to the system and will need to be assigned to a cluster. Initially there will not be any behavioral data for a new computer, therefore the administrator will have to assign it to a cluster manually. Thus clusters must have user-friendly descriptions that permit manual cluster assignments. Once the new computer has been active long enough, it can be automatically re-clustered. These and other changes in clusters should be approved by the administrator.

Alert information must be displayed to the administrator together with some notion of the accuracy and severity of the alert. In some cases the system may be able to immediately curtail the user’s action – e.g., block an HTTP request – while other cases might require human review. The appropriate course of action will inevitably depend on the operating context of the system (as controlled by the administrator).

Finally the administrator should be able to see information about the system state – our cloud based architecture will allow additional resources to be used for both training and classification. The administrator should be able to control these settings to adjust the system performance.

In order to make the BBAC system usable, presenting key data to the administrator is vital. The administrator must be able to assign new computers to clusters, select between classifiers, approve changes to clusters, and be alerted to suspicious behavior.

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