Andrew Guillory – Personal Statement

Besides my undergraduate research, a number of experiences have prepared me for and motivated me to pursue a PhD and ultimately a career in research; I think these experiences also show evidence of my abilities.

During the spring, summer, and fall semesters of 2004 I worked as a teaching assistant for a large introductory object oriented programming course at Georgia Tech. As a teaching assistant, I was responsible for grading homework and tests for a section of around 25 students, and, more importantly, leading weekly reviews along with a fellow teaching assistant for around 50 students and holding office hours in the commons area of the college of computing. I enjoyed the challenge of communicating computer science concepts to other students and the chance to develop my teaching abilities. One of the best things about the course I worked for is that it was a required course for several non computer science majors in addition to computer science majors. I've found that with non computer science majors it's all the more important to communicate concepts clearly and in terms of example applications since many of the students do not have a purely technical interest in the subject.

I've also had the opportunity to directly present my research work to my peers. The undergraduate college of computing research symposium mentioned in my research experience essay is attended not only by the faculty judges but also by a large number of undergraduate computer science students that pass through during the three hours to check out the posters and demos and, of course, eat some of the hundreds of free Krispy Kreme donuts. The experience was intense. I learned to first relate the practical applications and goals of my work before talking about the technical results—with the work properly motivated I was in fact surprised at how quickly students from other backgrounds understood the basic concepts of the work. Along with my teaching assistant experience, this has taught me the importance of properly framing the technical concepts in terms of practical value, and that, when properly presented the ability of a general audience to understand the concepts behind advanced technical topics should not be underestimated.

In the fall of 2005 I had the opportunity to talk about my work and undergraduate research in general with an even broader audience; I was asked by my advisor to present a poster as one of the representatives from the college of computing at the launch of a new campus wide undergraduate research program here at Georgia Tech. The event was open to students of all majors and held along one of the main campus walkways during class hours. Although I talked about the details of my work with those who were interested, the day was more about promoting undergraduate research work in general and talking to students about how they can get involved. This is something important to me since I've gotten so much out of my research work and would like others to share my experience; I think, even for students that are not planning to pursue graduate school or a career in research, the sort of critical thinking skills at the core of research are invaluable.

My undergraduate career has also afforded me professional experience working in groups on very large scale projects. Although not directly related to my research interests or career goals, I expect these experiences to benefit me. In the summer of 2005 I worked as a Software Design Engineer intern at Microsoft as part of the team creating the new version control system in Visual Studio Team System 2005. I wrote test tools for the team and later on in my internship started fixing bugs in the product. My work at Microsoft was valuable for two reasons. First, I gained practical experience working full time with a team on a very large code base. I feel that this sort of system building is in many ways inseparable from computer science—although it's not research in and of itself I think it is often times a necessary component of research. This is especially true in artificial intelligence as research becomes more ambitious with large scale projects like the DARPA Grand Challenge and RoboCup. Second, perhaps surprisingly, my time at Microsoft strengthened my resolve to pursue a PhD and a career in research. The team was great as was the working environment, but for me the work itself did not match the excitement of research

My ultimate career goal is a research position in my area of interest, either in a commercial lab or academic setting. I would prefer a position in an academic setting, because of the openness of academia as compared to commercial research and because I enjoy teaching. However, I feel my research has potential to directly benefit society aside from just advancing technical understanding. As discussed in my research proposal essay, the direct applications for learning models of behavior from observation are numerous. In my own work with Dr. Tucker Balch, we seek to enable ecologists to better understand the behavior of social insects—a situation of science helping science. Many researchers studying this problem hope to apply it to technology to help the elderly and people with disabilities; for example, Dr. Henry Kautz at the University of Washington studies activity recognition with for the purposes of what he calls assisted cognition—systems to help people with cognitive disorders. At the Human Dynamics lab in my proposed university, alumni Dr. Nuria Oliver researched assistive car driving technology as part of her PhD work, and current PhD student Michael Sung is examining applications in health monitoring. Researchers at the Human Dynamics lab have also investigated applications related to video surveillance which could directly benefit national and private security. A PhD is the next logical step towards achieving my career goal as it would allow me to continue to develop my research with the support of a research advisor and university.

Andrew Guillory – Previous Research Experience

I started working with Dr. Tucker Balch at Georgia Tech in the summer of 2004. I assumed development on a piece of software called TeamView used for editing, labeling, and playing back tracking data. I redesigned the interface to support a new timeline editing view, similar to audio and video editing software. This was not something Dr. Balch specifically asked me to do, but I felt it was necessary to support the new editing features Dr. Balch wanted to add. I've maintained and developed TeamView since then.

In the fall of 2004 I began working with Dr. Balch on research. The problem I investigated with him was the problem of creating human understandable, executable models from insect tracking data. By executable I mean a model which can be used to recreate the behavior of the agent in a simulation or on a robot. Such a technique could be used by ecologists, for example, to predict the behavior of social insects like bees or ants in different situations and to hopefully better understand the behavior. The project falls into Dr. Balch's larger Biotracking research initiative which has the goal of enabling animal behavior research through methods from robotics and artificial intelligence. At the time I began working on it, Dr. Balch did not have students working on this problem, and, although he had an idea of what type of model to use, there were still a number of open questions. As a first step towards solving this problem, Dr. Balch wanted to investigate the problem in a restricted case in which the low-level actions the agent performs are known and we simply want to learn the high-level structure of the behavior from unlabeled data—what causes the agent to switch between low-level actions.

I worked with Dr. Balch directly on the problem as my senior research project for the fall of 2004. This semester was primarily spent researching the model Dr. Balch proposed we use, Input/Output Hidden Markov Models (IOHMMs) which are a variant of standard Hidden Markov Models (HMMs) in which the transition and output distributions are conditional on input values. Explained in another way, IOHMMs are probabilistic finite state machines which can be trained through a variation of the standard HMM training algorithm, Expectation Maximization (EM). I did not at this point have a large amount of experience with machine learning in general or graphical models in specific, aside from an Introduction to Intelligent Systems course I had taken the previous year. As such I spent a large amount of time simply reading papers on HMMs and IOHMMs and independently implementing the standard training algorithms for them. By the end of this semester I mostly understood IOHMMs and had an idea how they could be used to solve the problem. Our use of IOHMMs as an executable model of an agent's behavior is to the best of our knowledge novel. Our particular variation of IOHMM incorporates known low-level actions by modeling the output distributions as mixtures over them and models the switching behavior with the conditional transition distributions. I demonstrated this to Dr. Balch with results learning an IOHMM from randomly generated sequences from another, known IOHMM.

Based on these early results, Dr. Balch hired me as a research assistant for the spring of 2005. That semester, our goal was to test the IOHMM learning on a slightly more complicated domain. Dr. Balch proposed we code by hand a simulation of a behavior loosely inspired by insect behavior and then see if we can recreate the behavior using an IOHMM learned from tracking data. By testing the learning on a simulated domain we can actually check the results of the IOHMM learning—that is by comparing the learned IOHMM to the original code for the simulation we can determine precisely the flaws in the IOHMM. It was my responsibility to code this simulation, run the experiments using my IOHMM code from the previous semester, and of course with Dr. Balch analyze the results. By the end of the semester we had results which showed that, assuming we know the low-level actions the agent performs, we can learn the high-level behavior of a simulated agent and reproduce the agents behavior from tracking data, with some flaws. I presented my research at the undergraduate college of computing research symposium that spring and was honored to win both first place judge's award and people's choice.

Around the end of the spring and beginning of the summer of 2005 I started collaborating with Dr. Charles Isbell on some of the machine learning aspects of the project. With Dr. Isbell I developed a new method for training our variation of IOHMM through discrete optimization, where we use discrete optimization to learn the mapping betweens states in our model and the low-level actions, running EM to evaluate the mapping at each step. This method is able to learn the correct structure of the behavior more quickly than simple repeated EM runs. Combined with our earlier results, we submitted a paper to major machine learning conference on which I was the first author. The paper was unfortunately not accepted, but the experience was very valuable for writing experience and the reviewer feedback. Portions of the paper also formed the basis of a section of a larger review paper outlining the Biotracking project as a whole, which has been accepted to Proceedings of the IEEE [1], on which I am a coauthor.

In the fall of 2005 I began working with another undergraduate, Hai Nguyen, who was brought onto the project by Dr. Balch to work on automatically learning the low-level actions of an agent from labeled data. I worked with Hai and Dr. Balch to combine our methods so that we could learn the entire behavior of a simulated agent from a mixture of labeled and unlabeled data. The effort has been mostly successful, and these combined results along with changes in response to feedback from the previous paper have formed a new conference paper which has been submitted for review, on which I am the first author. I feel with the new results and changes the paper is significantly stronger than our previously submitted conference paper. We are still actively working on improving our methods and, most importantly, applying them to real world data. We currently hope to apply the method to locust tracking data. Locusts exhibit two distinct low-level behavior states: solitary and gregarious behavior. We hope that by learning a model of the switching between these two states using our methods we can automatically build a simulation of locust behavior, with which we might be able to predict locust swarming behavior.

Publications

T. Balch, F. Dellaert, A. Feldman, A. Guillory, C. Isbell, Z. Khan, S. Pratt, A. Stein, H. Wilde. How A.I. and Multi-Robot Systems Research Will Accelerate Our Understanding of Social Animal Behavior. To appear in Proceedings of the IEEE, 2006 (Special Issue on Multi Robot Systems)

Andrew Guillory – Learning Executable Models of Behavior from Observation
Key Words: Machine Learning, Activity Recognition, Behavior Modeling
This is an original research proposal.

As a PhD candidate I am interested in machine learning applications for the problem of learning models of behavior from observation—similar to my research work as an undergraduate with but not necessarily focused on insect behavior. I am interested in applying and expanding the original methods I have developed with Dr. Tucker Balch as an undergraduate for learning a human understandable model which can be used to recreate behavior in a simulation—a different problem than learning a model for use in recognizing a behavior. Beyond studying insect behavior, these methods could be used, for example, to predict the behavior of human crowds or build executable models of a user's interactions with a software interface. I am also interested in training algorithms for models of behavior, especially discrete optimization methods for learning the structure of behavior. In my work with Dr. Charles Isbell I have experimented with a novel discrete optimization method for training our particular kind of executable model, but it is a heuristic method; I would like to better understand this method from a theoretical view and determine for what other kinds of models it might be applicable.

The majority of work in learning models of behavior could be classified as activity recognition. Models learned in activity recognition are sometimes generative, but usually do not model the agent's responses to the environment and are therefore inappropriate for recreating the activity. Example activity recognition work includes [1] from Dr. Balch's Biotracking project. My research work is more similar in purpose to work in imitation learning as in [2]. However, imitation learning generally focuses on low-level action learning as opposed to high-level structure learning, often under the physical constraints of a particular robot. There has been some other previous research outside of imitation learning that explicitly models an agent's responses to the environment. In [3] the authors recover from unlabeled data a control string in a motion description language. However, their work assumes the agent behaves deterministically, and the control string model cannot represent loops in control. The coupled Hidden Markov Models (HMMs) used in [4] are similar to the Input/Output Hidden Markov Models (IOHMMs) [5] used in my work, except that IOHMMs do not explicitly model the environment that the agent interacts with and have conditional output distributions as well as transition distributions. In [6] the authors recreate interactions between people, but the model used is not a state based model and is arguably not human understandable.

I would like to continue to develop the IOHMM based approach and apply it to real world data. It is my hypothesis that, not only are IOHMMs a more powerful model than typical activity recognition models in that they are able to recreate the behavior observed, but that they will also prove successful at learning the human understandable structure of behaviors on problems for which typical methods fail. I base this hypothesis on the power of the conditional transition distributions in IOHMMs which take into account the context of transitions between states. This is supported by some of my results with Dr. Balch and Dr. Isbell on simulated models where we found that HMMs performed unexpectedly worse than IOHMMs.

I would also like to continue to develop new learning algorithms for these types of models. The discrete optimization method that I developed with Dr. Isbell shows promise but is somewhat arbitrary in design. I think developing a better technical understanding of the algorithm, perhaps in terms of Markov Chain Monte Carlo (MCMC) sampling, will help justify the algorithm and explain why and when it works. I'd also like to investigate it's relation to the Expectation Maximization (EM) / MCMC algorithm in [7], which is very similar in that it also solves a discrete assignment problem coupled with EM based parameter estimation problem. It is my hypothesis that discrete optimization algorithms such as these will be the key to scaling up behavior learning to more complicated models. In our simulated experiments with IOHMMs we learned a 4 state behavior model, and single EM runs were only able to learn the correct structure around 20% of the time. With the discrete optimization method we were able to achieve rates of over 90% while only taking 3-4 times as long as a single run of EM.

The MIT Media Lab, particularly the Dr. Alex Pentland's Human Dynamics group, is best suited for carrying out this work. The Human Dynamics groups with is one of the most well respected groups in human behavior modeling, which is I think probably the most promising and important application of behavior modeling in general. I also feel that the IOHMM based approach matches nicely with previous work in the group, with the group's background in modeling interactions. As already mentioned, [5] and [6] are among the related body of work which explicitly model an agent's responses to the environment. In fact, the standard training algorithm for IOHMMs could be accurately described as a Conditional EM algorithm as discussed in [6]. I also am interested more recent work in the Reality Mining project and the LiveNet project.

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