Research

Introduction
My primary research area is machine learning and its applications to (1) affective computing, including automatic facial expression and emotion recognition, and (2) education, including automated teaching systems and optimization of students’ learning experience.

Modern education is changing rapidly. The near-ubiquity of computers and mobile devices, and the growth of high-quality educational content through websites such as edX, Coursera, and Khan Academy, are giving students more choices than ever. This leap in educational access brings great opportunity: not only can more students learn from more teachers, but teachers can learn from more students. Educational datasets of unprecedented size, consisting of billions of events from millions of students, are being collected of student participation and test performance [17, 21], and these can be data-mined to improve students’ learning experience.

In parallel to this surge in educational opportunity, the state of affective computing technology has progressed tremendously over the last 15 years. Automatic face detectors are now commonplace in mobile phones and cameras, and facial expression recognition is finding first commercial applications (e.g., Sony “Smile Shutter”). Over the next decade, affective computing may greatly alter the fields of computer gaming, market research, security, and education.

My research explores methods of automatically analyzing faces and measuring emotions, especially the emotional states relevant to learning such as engagement and frustration. I also study how machine learning can be used to improve education. For instance, automated student emotion recognition can be used as a real-time, unobtrusive feedback signal to teachers, both in standard classrooms and in online-learning environments. Analysis of student emotion data from massively open online courses (MOOCs) may also help identify parts of a lecture that are especially effective or need improvement. I am also interested in automated teaching systems, including the development of probabilistic learning and teaching models, and optimization of the teaching process using control-theoretic methods.

Synopsis of Prior Work
Machine learning for affective computing: My early graduate school research at the University of the Western Cape and the Machine Perception Laboratory at the University of California, San Diego, focused on affective computing and automated face analysis. In particular, I developed machine learning-based algorithms for real-time automatic face detection, head-pose estimation [2, 3], and facial expression classification [1]. My research contributed to the creation of one of the best smile detection systems to-date [7]. I also co-developed the Computer Expression Recognition Toolbox [4], a widely-used software toolkit for fully automatic facial expression analysis.

Key to creating these detectors was collecting datasets of millions of training images, and also obtaining high-quality training labels (e.g., the person is smiling/not smiling) by crowdsourcing them from the Amazon Mechanical Turk. Our laboratory was pioneering both in collecting realistic face image datasets [7], and in developing aggregation algorithms to improve label quality [5].

After graduating from UCSD, I spent 2 years as a co-founder, research scientist, and software engineer at the startup Emotient, where I co-developed software infrastructure for automating the collection of training data and accelerating the training of computer vision-based classifiers of emotion [27, 28].
**Machine learning for education**: From my life-long love of teaching, I became interested in how machine learning and affective computing could be useful in education. In 2008 I conducted a pilot study showing that a student’s facial expression, as recognized by an automatic classifier, is predictive of his/her perception of curriculum difficulty while watching a lecture video [9, 10]. The figure below shows: (a) a video lecture on the history of physics; (b) a student watching the lecture while her face is analyzed automatically for facial expression (shown in the graphs); and (c) the student’s self-reported perception of curriculum difficulty during the lecture, as well as automatically estimated values based on her facial expression.

In later work, I collaborated with Prof. Zewelanji Serpell at Virginia State University to study the role of students’ emotions in cognitive skills training tasks [6]. In particular, we developed a real-time vision-based detector of students’ “engagement” while learning, and showed that (1) the detector’s accuracy is comparable to that of human labelers, and (2) the detector’s outputs are predictive of students’ test performance (Pearson $r = 0.64, p < 0.05$) [8].

**Automated teaching**: Automated teaching systems have existed for over 50 years (e.g., [11, 12]), and some of the more prominent systems have taught mathematics to hundreds of thousands of students [18].
To date, most automated tutors are built by hand-crafting rules for how to teach the student. However, designing such rules manually becomes increasingly difficult as more complex sensors such as web-cameras are introduced, and as more complex models of how students learn are employed. An alternative approach is to formulate “teaching” as an optimal control problem, and to use methods from machine learning and control theory to find an approximately optimal solution. At UCSD I explored this approach and developed an automated foreign vocabulary teacher that uses images to exemplify and teach the words’ meanings [14], similar to Rosetta Stone [15]. The system makes teaching decisions -- e.g., which word to teach next, or which images to show for the next word -- so as to minimize the expected remaining time-to-mastery. In an experiment on 90 human subjects, the optimized teacher helped students learn the vocabulary 24% faster than a baseline teaching strategy.

Automatic intervention in MOOC student dropout: An important research question for MOOC providers such as edX and Coursera is how to boost student persistence so that students who want to complete a MOOC actually do so [21]. In ongoing work at Harvard, together with Dr. Justin Reich, I am using machine learning to analyze millions of students’ event logs to develop computational tools not only to predict which students will drop out, but also to intervene before they quit. For example, students who struggle to answer many practice problems correctly can be automatically offered help from a MOOC teaching assistant. Prediction of student dropout is a difficult machine learning problem (e.g., [23, 24]), and automatic intervention is an even more challenging control problem.

Future Research Agenda
As an assistant professor my research agenda will include the following projects, all of which are amenable to participation by both graduate and undergraduate students:

Development of Affect-Sensitive Automated Tutoring Systems: One of the key challenges in automated teaching is to build systems that can automatically sense and respond to students’ affective states, such as engagement, boredom, or frustration, so as to teach more effectively. While important progress has been made in both detecting these states [8, 26] and responding to them [13, 25], so far the demonstrated educational benefits have been very meager [13]. More sophisticated control-theoretic approaches to incorporating affective state estimates into the teaching controller may be needed.

Tutoring at Scale: One-on-one tutoring from an expert teacher is widely considered to be the most effective method of teaching [22]. One reason for its effectiveness is that students receive specific and immediate feedback to their particular confusions and misunderstandings when learning a new topic. However, for many students the cost of private tutoring is prohibitively expensive. One way of mitigating this high cost is to record and index a large number of instructional videos from thousands of teachers across the Web, spanning hundreds of didactic approaches, for key concepts and misconceptions within an academic domain. By intelligently matching students’ questions with the available explanations for a particular topic, it is possible that much of the benefit of one-on-one tutoring could be offered at a fraction of the cost.

Improvement of Educational Content Using Student Emotion Feedback: The ability to measure students’ engagement and frustration opens the opportunity to create “heat-maps” of which parts of a video lecture or electronic textbook are most effective or need improvement. A key challenge is to devise a methodology for how to use these heat-maps iteratively to improve educational content.
Calibrating Detectors to Individual Users: An important challenge for the machine learning and computer vision communities is to develop classifiers that can be “tuned” to a particular environment without needing to be retrained from scratch. An automatic “frustration” detector, for example, might perform well on average but perform very badly on particular persons or in certain lighting conditions. It would be useful to enable users to provide sparse feedback to the detector for images on which the classifier made a mistake, and thereby improve the classifier’s outputs on subsequent images.

Summary
For the past 10 years I have helped to advance the fields of automatic emotion recognition and automated teaching, primarily in academia but also in industry. My future research agenda tackles problems in the intersection of these two growing fields, with the practical goal of improving education in conventional classrooms, distance-learning environments, MOOCs, and automated teaching systems.

References


