

A Sustainable Model for Integrating Current Topics in Machine Learning Research into the Undergraduate Curriculum

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Abstract— This paper presents an integrated research and teaching model that has resulted from an NSF-funded effort to introduce results of current Machine Learning research into the engineering and computer science curriculum at the University of Central Florida (UCF). While in-depth exposure to current topics in Machine Learning has traditionally occurred at the graduate level, the model developed affords an innovative and feasible approach to expanding the depth of coverage in research topics to undergraduate students. The model has been self-sustaining as evidenced by its continued operation during years after the NSF grant's expiration and is transferable to other institutions due to its use of modular and faculty-specific technical content. This offers a tightly-coupled teaching and research approach to exposing current topics in Machine Learning research to undergraduates while also involving them in the research process itself. The approach has provided new mechanisms to increase faculty participation in undergraduate research, has exposed approximately 15 undergraduates annually to research at UCF, and has increased preparation of a number of these students for graduate study through active involvement in the research process and co-authoring of publications.

Index Terms— Undergraduate Research Experiences, Team Teaching Models, Curriculum Development, Integrated Research and Teaching, Machine Learning.

I. INTRODUCTION

Current models of undergraduate research such as *Research Experiences for Undergraduate Students (REU)*, Honors Theses, and senior year projects frequently serve as effective means to introduce undergraduate students to research [1]. However, these interactions can reveal challenges with regards to sustaining undergraduate research over an extended period of time [2]. The *Sustainable Model for Assimilating Research and Teaching (SMART)* at UCF

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integrates current research in into the undergraduate curriculum through a course sequence that has propagated beyond an NSF-funded *Combined Research and Curriculum Development (CRCD)* award [3][4]. SMART reaches a wide audience of undergraduate students who may not otherwise have considered well-established research programs for undergraduates, such as the NSF-funded Research Experiences for Undergraduates (REUs). The effort described here is a structured approach with a focus on Machine Learning (ML), spanning multiple faculty members with various ML research interests. This approach has encouraged undergraduate students to pursue graduate education, while producing research results and outcomes which have advanced the professional development of students and faculty members involved.

Faculty members will frequently work individually with undergraduate students on topics that are related to their own research. However, the proposed SMART approach provides research-oriented, team-taught course offerings that span multiple topics. This exposes undergraduate students to a wider breadth of research experiences. The team-taught course offerings benefit the faculty involved in this effort by encouraging collaboration of faculty with similar research interests, and by providing a structured and sustainable mechanism for recruiting undergraduate students in their graduate research teams. Additionally, these provide a neutral, collaborative environment for senior faculty to mentor junior faculty in a non-intrusive fashion.

An overview of the SMART method is shown in Figure 1. This framework was realized during the NSF CRCD grant's funding years of 2002 through 2005, and sustained thereafter. Part of the CRCD effort involved developing and teaching modules, i.e., appropriately chosen homework assignments, in required undergraduate courses to encourage students to register for the senior level courses called *Current Topics in Machine Learning I (CTML-I)* and *Current Topics in*

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Machine Learning II (CTML-II). In *CTML-I* the students learn the fundamentals of the current research topics from the faculty members who are co-teaching the course. In *CTML-II* those students who continue participate in a hands-on research project. Students work one-to-one with a SMART faculty member, either individually or in small groups, along with an appropriately-chosen graduate student mentor. During the NSF grant's funding period, an advisory board of faculty and industrial members acted as facilitators and evaluators of this effort, and provided valuable feedback leading to the *SMART* model. The *CTML-I* and *CTML-II* classes have been consistently taught since the Fall semester of 2003 facilitating exposure to a significant number of undergraduate engineering and computer science students.

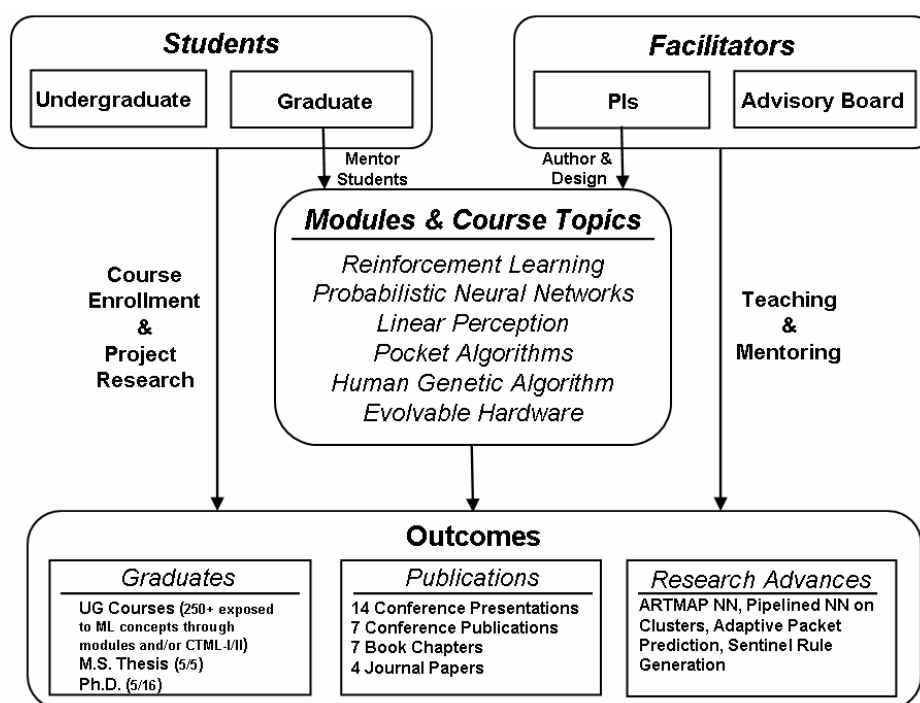


Figure 1: SMART Project Framework

II. RELATED WORK

While many faculty members strive to integrate their research into undergraduate experiences on an individual basis or research team basis [5], [6], [7], the availability of a structured approach

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that spans multiple faculty and multiple semesters can be beneficial. The longer-term research relationships that are created between faculty members and undergraduate students through this long-term approach can be synergistic with other initiatives, such as summer internship programs [2] and the NSF REU under the direction of a research professor. Initial student perception of the value of REU programs has been overwhelmingly positive [1]. However, the REU program is mostly centered around performance of research, with little time devoted to classroom learning on the research topic or methods. Furthermore, some have found that the 10-week duration of a summer REU experience may be insufficient to fully convey the essence of technical research that leading to publishable results [2][8].

Team-based teaching has previously been integrated into undergraduate curricula on a number of topics, but quite often for encouraging a multidisciplinary approach [10][11] or redistributing faculty workload [9]. On the other-hand, team-teaching in *CTML-I* introduces students to a range of current ML research topics, as well as to the research styles of a variety of faculty members. This exposure can assist students in their decision to consider a research apprenticeship with one of these faculty members. Several other CRCD projects have been funded by NSF such as ones in particle technology at NJIT [12]; sensor materials at Ohio State [13]; optical sciences at NAT [14]; convex optimization for engineering analysis at Stanford [15] and smart materials at Texas A&M [16] but have not focused on creation of portable sustainable model. CRCD programs have the ability to more fully immerse a student because they avoid the time limitation of a summer term imposed by NSF REU programs. While the focus of SMART has been on ML, the model can be applied to other topics and at other institutions without the need for NSF funds to initiate it. This model requires only a small nucleus of faculty with similar research interests and the motivation to co-teach courses similar to the *CTML-I* and *CTML-II*

courses described here.

III. RESEARCH AND CURRICULUM INTEGRATION APPROACH

The SMART initiative involves multiple mechanisms beyond those originally incubated by a CRCD award [17] – [22]. In the SMART approach, faculty members initiate the process via two alternative techniques. First, availability of the program is broadcast through seminars and workshops to students. Second, technical learning modules are delivered in select required undergraduate courses. Modules highlight current ML topics as application examples that students already learn, such as data structures. Both techniques attract undergraduate students to become involved in ML research, bootstrapping our integrated teaching and research method.

A. SMART Teaching and Research Methodology

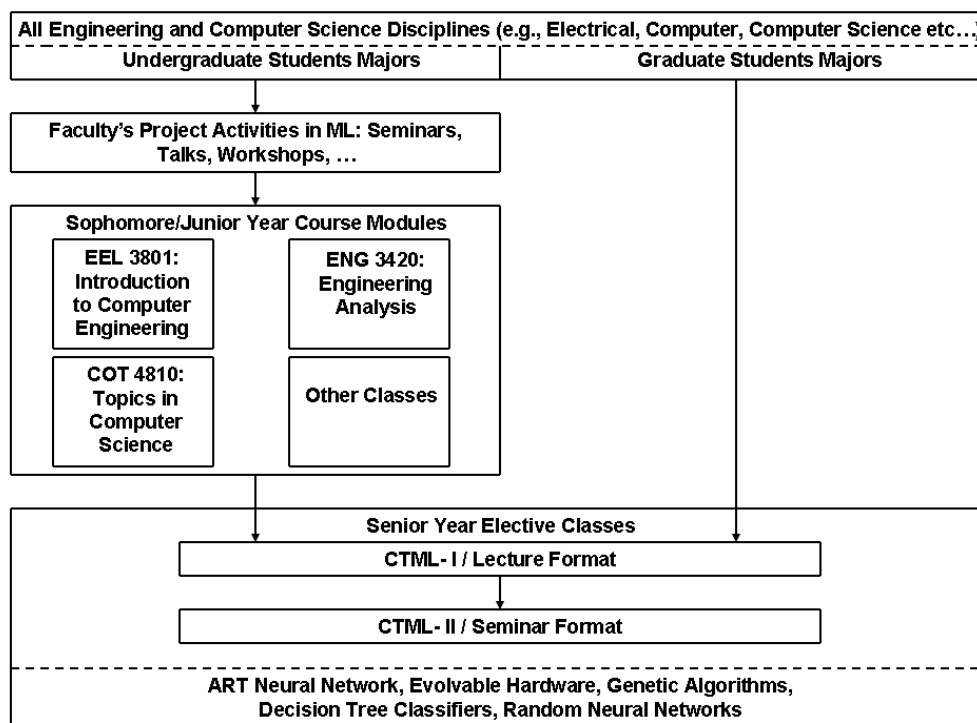


Figure 2: SMART Activities to integrate ML research into Education.

As shown in Figure 2, ML-related seminars, guest-lectures, one-to-one interactions with students, and ML modules, offered by SMART faculty members, are one of the many vehicles

used by SMART faculty to encourage students to register for the CTML-I and CTML-II senior level courses. *CTML-I* introduces students to research faculty and topics. It leads to *CTML-II*, where students engage in research projects advised by a faculty member who co-taught in *CTML-I*. Both courses are electives in the degree program, and a number of disciplines in engineering and computer science allow their students to register for such technical electives. *CTML-I* emphasizes lecture-based instruction on current ML concepts of interest to the team of participating faculty, and *CTML-II* stresses hands-on research by undergraduate students working with a graduate student mentor while being actively advised by a faculty member. The course sequence helps to address challenges cited in alternate experiences with undergraduate research, especially recruitment of skilled students matched to faculty interests [23][24].

The broad cross section of research interests in ML make it a suitable candidate for co-teaching of courses. In the School of Electrical Engineering and Computer Science at UCF, there are currently eight faculty members with significant interests in AI and ML, and at least three other faculty members who apply these techniques to applications. This constitutes a sufficiently large nucleus of faculty expertise with diverse research interests to sustain the continual offering of *CTML-I* and *CTML-II*. Since initiation, two additional new faculty hires from the Computer Science program voluntarily enlisted in the SMART initiative. Furthermore, the initial proposal effort included a faculty member from the Education Department helped in the design of the evaluation instruments, and in the assessment of the project's accomplishments.

B. SMART People and Timeline

In order to achieve the goal of introducing undergraduate students to leading-edge research in ML, two objectives were pursued. The first objective is the creation and continuous offering of *CTML-I* and *CTML-II* that have now become permanent listings in the university catalog. The

second objective is the task of making students aware of the CTML-I and CTML-II opportunities. The most noteworthy of which was the creation of *Machine Learning modules* that can be inserted in select sophomore and junior level undergraduate classes.

A 3-year timeline required to establish a self-sustaining program is depicted in Figure 3. Various semesters, since Fall 2002 have been devoted to course material development, project material development, as well as teaching, assessing and improving our course content and educational practices. CTML-I and CTML-II have consistently been offered to conduct teaching, assessing and improvement of both classes.

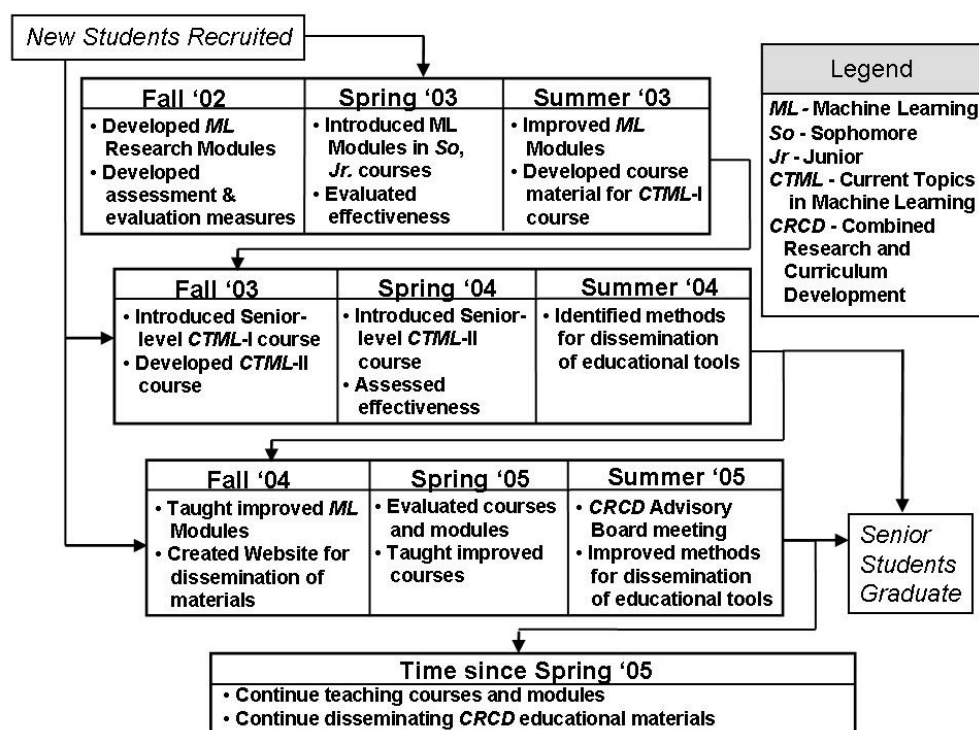


Figure 3: SMART Timeline of Activities throughout the funding period to establish the model.

As shown, most of the initial effort was expended in the design of the educational materials for the research modules and the CTML-I lecture notes, as well as in the advising of the students in research projects assigned in the CTML-II course. The CTML-I class is taught each Fall by a team of faculty which allows them to provide students with the necessary background to join in

the faculty member's current research efforts. The CTML-II class is taught each Spring by the same faculty who taught CTML-I in the previous Fall. Interested students from the CTML-I class, as well as a few new students, work one-on-one with a faculty of their choice on an ML research project and may also receive mentoring from a faculty's graduate students.

C. Curricular Content and Student Projects

1) Machine Learning Modules

The ML course modules applied throughout the sophomore and junior year undergraduate courses can stimulate student interest in ML topics through application examples of elementary technical concepts required for the degree program. Modules developed as part of the project introduces students to some widely used algorithms for ML and their underlying principles. As an ongoing effort, these modules were refined and improved based on feedback from the students such as the examples listed below:

- *EEL 3801 - Introduction to Computer Engineering* – Module: "Learning the Trick of the Game called Nim"
- *EGN 3420 - Engineering Analysis*– Module: "Perceptron-Based Learning Algorithms/The Pocket Algorithm"
- *EEL 4851 - Data Structures* – Modules: "Graph and Network Data Structures for Evolvable Hardware" and "Inductive Learning Algorithms"
- *COT 4810 - Topics in Computer Science*– Module: "Human GA: Learning Evolutionary Computation via Role Playing"

More details about the specifics of each one of the aforementioned modules and student feedback are provided in [3]. Because of space limitations, this article focuses on the *CTML-I* and *CTML-II* classes. Advocacy of the SMART program by means of invited speakers, posters, and presentations to interested student groups such as senior design students and at graduate pre-recruitment seminars have also had a positive impacts on enrollment.

2) Current Topics in Machine Learning I

In any course, one must consider the tradeoff between breadth and depth. Traditional courses

tend to focus on breadth, providing students with knowledge of many well-known and fundamental algorithms. The CTML-I class, on the other hand, emphasizes depth in specific research areas in order to better prepare students to actively join an ongoing research project through a bottom-up learning approach. Depending on the faculty involved in CTML-I, the topics covered in the course may not span all traditional machine learning algorithms. The philosophy adopted, which has been quite successful, is that involvement in an actual ML research will spark student interest to further investigate the breadth of ML algorithms in the future.

The CTML-I course features introductions to the research topics presented on a rolling basis by a group of faculty. Each faculty member presents five, twice-weekly, lectures on their topic of expertise. The teaching materials for CTML-I are derived almost exclusively from peer-reviewed publications of the SMART faculty and their other publications such as books or tutorials on *Adaptive Resonance Theory (ART)* neural networks [25] or decision trees [26]. For instance, the ART topic is elaborated below as an example.

a) Adaptive Resonance Theory (ART) Neural Networks

The students are first briefly introduced to neural networks because some may not have yet been exposed to this topic from the corresponding course module. Next, the students are exposed to the motivation behind ART neural network architectures and their specific parameters. The lectures are then devoted to discussing a benchmark ART neural network architecture, called *Fuzzy ARTMAP*, which is extensively used in solving classification problems. By understanding Fuzzy ARTMAP the student has the ability to quickly comprehend a number of other ART architectures. Furthermore, in the ART lectures, useful analogies are drawn between these basic ART architectures and other neural network architectures, such as multi-layer perceptrons and

radial basis function neural networks. Finally, successful applications of ART neural network are discussed, and the students are encouraged to study additional ART-related papers.

b) Homework Assignments in CTML-I

Homework is assigned for every major topic discussed in the CTML-I class. This assignment is designed to reinforce some of the important concepts discussed in class, and ranges from paper and pencil assignments to running experimental simulations. For example, one such assignment involves walking through the process of a training cycle of a Fuzzy ARTMAP neural network for a simple example. Another assignment involves using existing Genetic Algorithm (GA) code to study the impact of parameter settings on GA performance.

3) Current Topics in Machine Learning II

The first two weeks are devoted to a discussion of the projects that the faculty advisors propose to the students as potential research projects. In each lecture, the challenges posed as well as techniques to complete the proposed project are presented. After this two-week period, the students choose a research project of interest and work with the associated faculty member on a one-to-one basis. Example projects include various ML applications, experimentation on novel ML approaches, comparisons of two or more ML approaches on a class of application problems, and others. The research conducted in CTML-II always leads to a formal report, and occasionally to an honors thesis, and frequently a peer-reviewed publication.

a) Student Research Projects in the Current Topics in Machine Learning II

Students work on their chosen projects in groups of one to three. Each group of students is supervised by a faculty member and a graduate student mentor. Students are actively encouraged to form multi-disciplinary groups to emphasize collaborative work. Projects are completed over a 12-week period under weekly supervision by a faculty member and more frequent interaction with

a graduate student mentor. Monthly course-wide meetings are conducted in which students report progress and receive feedback from all participating faculty and students about their research. Students present their work incrementally at three presentation milestones. In the first presentation, students present a literature survey, requirements overview, proposed technical approach, and schedule. In the second presentation held one month later, students present an overview of the design progress to date, and solicit advice for possible solutions to technical issues from other student groups and faculty mentors. In the third presentation, held during final exam week, students present results and conclusions. Students must submit a final project report on their work using the IEEE conference article format. The quality of the presentations, the technical report, and the interactions of faculty and graduate student mentors with the student contribute to the grade of the student in the CTML-II class.

Table I: Examples of Student Projects and Publications

Project Title	No. of Students	Honors Thesis Produced	Conference Papers Published	Journal Papers Published
1. <i>Comparison of ssFAM and sssFAM Classifiers</i>	3	0	1	0
2. <i>Comparison of GAM, micro-ARTMAP, ssFAM, ssEAM and ssGAM Classifiers</i>	1	0	2	1
3. <i>Pipelining of Fuzzy ARTMAP Neural Networks without Match-Tracking</i>	1	0	1	2
4. <i>Hilbert Space Filing Curve Nearest Neighbor</i>	1	1	1	0
5. <i>Experiments with the Probabilistic Neural Network: Implementation on Beowulf Cluster</i>	3	0	2	0
6. <i>Backward Adjustments with the C4.5 Decision Tree Algorithm</i>	1	1	1	0
...				
32. <i>Voting Schemes to Enhance Evolutionary Repair in Reconfigurable Logic Devices</i>	1	0	1	0

Table I lists some examples of projects completed by students in CTML-II. Project 3 is an example of a joint effort by an undergraduate student and a graduate student mentor involving the parallelization of Fuzzy ARTMAP on a Beowulf cluster which improved the convergence speed of the training process on large databases. The undergraduate student implemented Fuzzy

ARTMAP on the Beowulf cluster and generating experimental results that demonstrated the effectiveness. Results were published in two conference papers and two journal papers, all of which were co-authored by the undergraduate student. This student was later accepted into the Ph.D. program at UCF and received an NSF Graduate Research Fellowship, one of the most prestigious fellowships in the nation for recognition of student research potential.

IV. RESULTS AND ASSESSMENT

Assessment of the SMART model for undergraduate research and curriculum begins with measuring of the effectiveness of student recruitment and retention. Table II depicts the number of students who have registered for the CTML-I and CTML-II courses each semester. A total of 97 students have completed or are in the process of completing these courses. Since some of the students took both CTML-I and CTML-II, 77 distinct students have been introduced to research through the CTML-I and CTML-II sequence over this 5-year span.

Year Offered	Number of Students	
	CTML – I (Fall Semester)	CTML – II (Spring Semester)
2003 – 2004 *	11	12
2004 – 2005 *	10	8
2005 – 2006 *	13	6
2006 – 2007	14	8
2007 – 2008	10	5

Table II: Number of students in the CTML-I and CTML-II courses.

* denotes years of CRCO NSF funding

The effectiveness of the CTML-I and CTML-II courses can be gauged by a number of indirect measures such as student survey questionnaires and direct measures, such as presentations and final reports. Furthermore, students' works have been judged as a direct measure by an independent group of evaluators who comprise the Advisory Board. Also, some of our students' work has been accepted for publication in peer-reviewed conference and journal venues, which

provides another direct measure of their ability to perform research of publishable quality. Finally, information about the impact that SMART had on faculty culture is described below.

A. *CTML I Course Assessment and Evaluation*

The learner outcomes for the CTML-I course are measured using a survey at the end of the course that probes students' understanding of the concepts and their confidence in applying the concepts learned. The CTML-I course lectures focus on ML topics such as ART Neural Networks, Genetic Algorithms, Decision Tree Classifiers, Inductive Learning, and Evolvable Hardware. At the end of each course topic, the students are quizzed with some questions gauging their understanding of the fundamental concepts, and others evaluating their ability to apply the concepts learned in class to solving problems, or extending the presented solutions. Students are able to respond with how well the objective was met through questions such as:

- I can explain the basic steps that occur in each generation of a GA
- I can discriminate between the one-classifier and the multiple classifier results within the application domain of the letters database

In the offerings of the CTML-I courses from Fall 03 to Fall 05, more than 60% of the students perceived that they understand the concepts. Cumulative results across the topics are presented in Figure 4. Results show that 72% of the students stated an understanding of the concepts presented, with less than 6% of the students expressing failure to understand some of the concepts. These include responses from 33 students over the three-year period.

In order to measure the skills learned by the students and their confidence in applying these skills, as well as extending their understanding to real-life problems, questions included:

- I can apply the major steps of FAM's performance phase to given examples
- I feel comfortable in writing code that implements the growing phase of a decision tree classifier

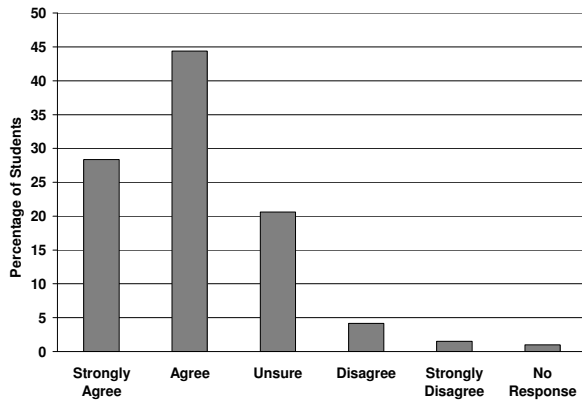


Figure 4: Cumulative Learner Outcomes – Comprehension of Concepts

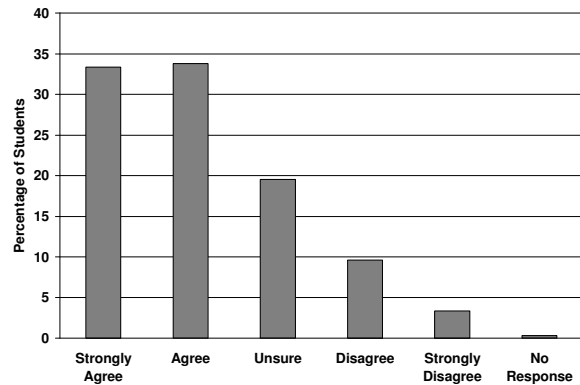


Figure 5: Cumulative Learner Outcomes – Applying Techniques

The cumulative results of the survey questionnaire responses, over a three year period are provided in Figure 5. It shows that 67% of the students express confidence in applying their newly acquired skills, with 13% expressing concern in applying these skills.

B. CTML II Course Assessment and Evaluation

The performance of the students in the CTML-II course is assessed through their formal presentations, the one-to-one interaction with the faculty and the graduate student mentor, and through the technical reports that they produce for faculty review. The performance of the students in the CTML-II class was very encouraging. The participants in the SMART initiative have produced a total of four journal publications, 14 conference publications and presentations, and seven book chapters (see for example [27] – [31]). Journal papers co-authored by SMART undergraduate students include works on parallelization [32] and pipelining of Fuzzy ARTMAP [33], gap-based estimation [34] and experiments with micro-ARTMAP [35]. Three out of the four journal publications appeared in journal venues with a high impact factor. Neural Networks has impact factor of 2.0 and is ranked 16, while Neural Computation has impact factor of 2.6 with a rank of 14 in the list of highest impact factor AI journals (2006, Journal Citation Reports - Science Edition). Furthermore, the number of publications produced out of 35 CTML-II

students is 18, with four journals, seven conference papers and seven book chapters. These publications represented 23 machine learning projects in the CTML-II classes of Spring 2004, 2005, 2006, and 2007. This is a high publication percentage for undergraduate students at 52%. It is very competitive with the publication percentages of some of the most successful NSF REU programs in the nation. For example, the Computer Vision REU by Professor Mubarak Shah at UCF (<http://server.cs.ucf.edu/~vision/>) lists 60 publications in its 20 years of existence of that REU effort, involving 200 students, which results in a publication rate of 30% assuming that every student worked on a different project (see also [8]).

C. Advisory Board Assessment and Evaluation

The students' performance was also evaluated by the Advisory Board at a symposium held in 2005 that was comprised of academics and government/industry professionals with expertise in ML and its applications. These included 13 faculty members from related departments at the Florida Institute of Technology, University of Nevada Reno, Florida State University, United States Military Academy, University of Puerto Rico, University of Hartford, University of New Mexico, and Technological Educational Institution of Kavala, Greece, as well as several professionals working for national research laboratories such as the NASA Ames Laboratory, and Los Alamos National Laboratories, and research and development organizations such as Soar Technology and SAIC, Inc.

The board was requested to assess and evaluate our curriculum development efforts and their effect on the students' critical thinking, intellectual growth, and communication skills. Board members were provided in advance with a packet containing information about the ML modules, the CTML I and II courses, and the Assessment and Evaluation rubrics prepared by the SMART

faculty from the Education Department². The Advisory Board members assessed three elements of the SMART experience: (a) knowledge transfer in CTML-I, (b) knowledge transfer in CTML-II, and (c) potential for institutionalizing and disseminating SMART.

Eight of the student projects, conducted in the academic years 2003-2004 and 2004-2005, were presented during the symposium. Later, the faculty met with the Advisory Board to receive their comments regarding the SMART experience, based on a day-long interaction with the students. The responses of the Advisory Board to the Assessment and Evaluation rubric are listed in Figure 6. The answers to each of the 11 questions were: *Excellent*, *Good*, *Adequate*, and *Poor* with Questions 1, 3, 4, 5, 6, 10, and 11 receiving predominantly *Excellent* responses. Questions 2, 7, and 8 received primarily *Good* responses and Question 9 had some *Adequate* responses.

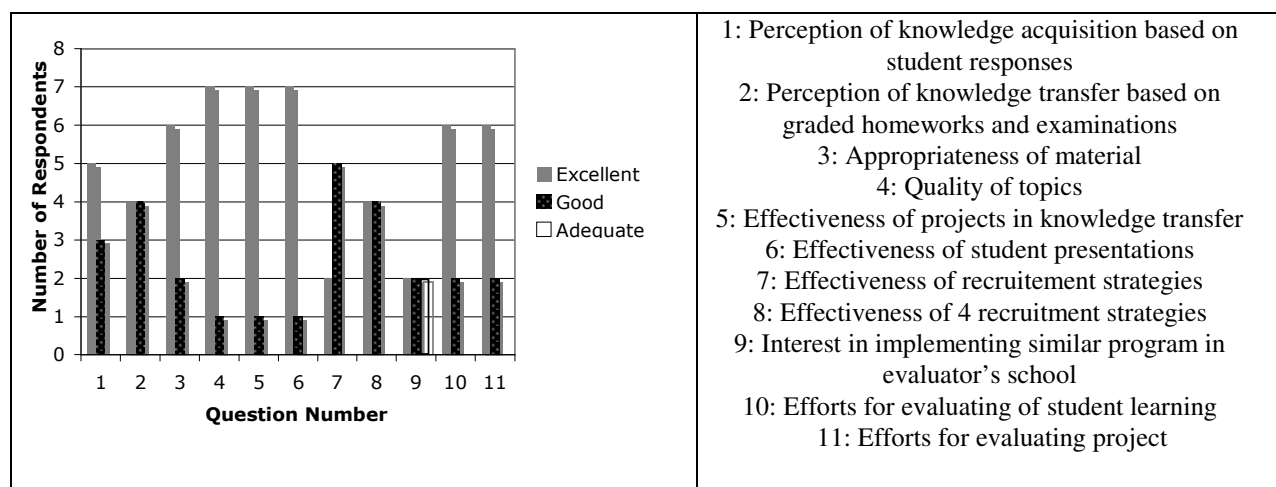


Figure 6: Responses of the CRCD Advisory Board Assessment and Evaluation rubric.

The board pointed out that some of the unique things about the SMART initiative at UCF are that there is a well-tuned team-teaching process in CTML-I, and that SMART students are highly motivated to do the Machine Learning project work in CTML-II. They also mentioned that important aspects of administrative burden rests on a few faculty. These concerns have been

² available at http://ml.cecs.ucf.edu/crcd/symposium/CRCD_Symposium_Evaluations/CRCD_Project_Evaluation_Rubric.doc

managed, since the *CTML-I* and *CTML-II* courses have been successfully conducted for three consecutive years after funding expired.

D. Impact on Students

The impact of SMART exposure on the undergraduate students has been significant. A total of 77 distinct students have participated in the *CTML-I* and *CTML-II* classes from Fall 2002 to Spring 2008. These students have been exposed to the Machine Learning research from a number of professors. Out of the 77 distinct students, 40 students have participated in Machine Learning projects with individual professors registered for *CTML-II*. Thirty five of these students have completed *CTML-II* projects for a total of 23 projects, some of which were group projects, and published their results at a rate of more than 50%. The specific numbers of students who took the *CTML-II* class from Spring 2004 to Spring 2008 and their current status are tabulated in Table III. Of the 40 students who completed the *CTML-II* class, 35 were undergraduates and 5 were graduate students. The proportion of participating undergraduates who continued to graduate school is 88% which is much higher than the 60% of non-participating undergraduates who had even expressed a possible interest in pursuing a graduate degree after graduation based on 2006-2007 graduating senior data from the UCF College of Engineering and Computer Science (CECS).

Two of the SMART program students have received the prestigious National Science Foundation Graduate Research Fellowship, while four other students who worked on a project in the Spring of 2007 placed first in the AAI-07 Video Competition for their “Dance Evolution” project. This competition was organized by AAI, a first-tier reputation conference, to encourage public promotion of AI. Furthermore, a number of graduate students (16 Ph.D.’s and 5 Master students) have developed professionally through SMART. Of the graduate students, all

five Masters and six Ph.D. students have already graduated, while the remaining nine Ph.D. students are pursuing their degrees at UCF, and one pursuing a Ph.D. at the University of Florida.

Table III: CTML-II students' pursuits after graduation.

Semester	# CTML-II Students	Grad School	Industry	Still an UG
Spring 2004	13 (4 G; 9 UG)	7 out of 9	2 out of 9	None
Spring 2005	8 (8 UG)	6 out of 8	2 out of 8	None
Spring 2006	6 (5 UG; 1 G)	5 out of 5	None	None
Spring 2007	8 (7 UG)	3 out of 8	1 out of 8	4 out of 8
Spring 2008	5 (5 UG)	None	None	5 out of 5

E. Impact on Faculty, Institutionalization and Dissemination

Since initiation of the effort, a total of six faculty have participated. Four of the six faculty have taught lectures in CTML-I and advised students in CTML-II during multiple semesters. This highlights the possibility for participating faculty to contribute based on their current availability. Furthermore, two new faculty hires have also voluntarily opted to teach CTML-I and advise students in CTML-II. Given the availability of eight ML faculty, and three additional faculty members who use machine learning algorithms for computer vision applications, in the School of EECS alone, the institutionalization of the SMART effort can continue despite faculty attrition or leaves of absence.

SMART has had a significant impact on the faculty members involved. For instance, one senior faculty member involved with the SMART initiative had not involved any undergraduate students in his research before CRCDD's initiation. Six years later, this faculty has involved over 40 undergraduate students in Machine Learning research through the SMART initiative and other NSF-funded educational efforts. On a related note, one of the junior faculty was able to advise a team of five undergraduates to attain recognition at the AAAI 2007 conference for *Best AI video*. In general, SMART has provided an effective mechanism for new or senior faculty to staff their research laboratories with highly motivated and pre-trained students. The cumulative

effect of SMART and its continued efforts to integrate research in education, cannot be understated, considering that only 20% of CECS faculty involve undergraduate students in their research based on 2006-2007 data through traditional methods.

Finally, one of the members of the CRCD Advisory Board who is also a faculty member at the University of Hartford, has integrated some of the SMART techniques at her institution by incorporating ML modules in an undergraduate class. Additionally, two other undergraduate institutions, Central Connecticut State University and Gettysburg College, have adopted a variation of the SMART model through a CCLI Phase I effort funded by NSF in 2004. In 2007, University of Hartford received a second phase CCLI Phase II effort facilitating expansion of the model to a larger number of undergraduate institutions. For more details about those efforts, please consult <http://uhaweb.hartford.edu/compsci/ccli>.

V. SUMMARY AND CONCLUSION

An effort which began as a multiyear CRCD project funded by NSF at UCF in 2002 has led to the development and refinement of an innovative and feasible approach to integrating research into the curriculum. The resulting SMART framework has been sustainable and there are now two elective undergraduate courses, CTML-I and CTML-II. CTML-I is offered each Fall semester and CTML-II is offered each Spring semester. They have secured steady enrollments and research involvement, even after the CRCD grant's expiration. These classes are regularly populated by approximately 10-15 students in CTML-I and by 6-8 students in CTML-II. Through advocacy of these classes to undergraduate courses and students by SMART faculty it is expected that the interest in these classes will continue in future years. A total of eight faculty have already co-taught these classes, four of whom have taught these classes multiple times. Furthermore, there is a nucleus of eight faculty members with strong ML interests in the School

of EECS at UCF. These attributes make the yearly offering of these classes possible.

The publication rate of students involved in the CTML-I and CTML-II courses is higher than that of the longest running REU program, a fact that makes this SMART effort appealing to both new students and new faculty. Furthermore, the percentage of SMART students who attend graduate school is high, which is an additional incentive of new faculty for getting involved with SMART. A key contribution of this work is the presentation of a model to introduce current topics of research in undergraduate education. This model can be disseminated to other research institutions that have a strong nucleus of faculty with common research interests. Moreover, the dissemination capability of this model to other institutions, like 4-year colleges, cannot be underestimated as Professor Russell's work at the University of Hartford has demonstrated³.

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