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Article

Developing Student Collaborations across Disciplines, Distances, and Institutions

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Because quantitative biology requires skills and concepts from a disparate collection of different disciplines, the scientists of the near future will increasingly need to rely on collaborations to produce results. Correspondingly, students in disciplines impacted by quantitative biology will need to be taught how to create and engage in such collaborations. In response to this important curricular need, East Tennessee State University and Georgia Technological University/Emory University cooperated in an unprecedented curricular experiment in which theoretically oriented students at East Tennessee State designed biophysical models that were implemented and tested experimentally by biomedical engineers at the Wallace H. Coulter Department of Biomedical Engineering at Georgia Technological University and Emory University. Implementing the collaborations between two institutions allowed an assessment of the student collaborations from before the groups of students had met for the first time until after they had finished their projects, thus providing insight about the formation and conduct of such collaborations that could not have been obtained otherwise.

INTRODUCTION

Even if a majority of the numerous efforts to transform undergraduate biology education are successful, there is no expectation that the biologist of the near future will be an expert in several different scientific fields. Instead, the new biologist is envisioned as a "scientist with a deep knowledge in one discipline and a working fluency in several others" (Labov *et al.*, 2010). The BIO 2010 report (National Research Council, 2003), for example, includes topics and skills in chemistry, physics, computer science, and mathematics that traditional majors in those respective fields do not experience before their senior year. Indeed, current efforts tend to focus on creating integrated, introductory curricula common to several majors (mathematics, biology, and computer science) that indicate how fundamental ideas in each discipline contribute to the understanding of the life sciences (Bialek and Botstein, 2004; Knisley *et al.*, 2010; Moore *et al.*, 2010). Researchers likewise tend to become conversant in other fields while remaining an expert in only one or two fields (Kuczenski *et al.*, 2005).

Consequently, at the heart of the ongoing quantitative biology revolution is the need to address problems via productive collaborations among individuals from a wide variety of disparate backgrounds (Salazar *et al.*, 2006). Molecular biologists, for example, are partnering with computer scientists and mathematicians (Kuczenski *et al.*, 2005), physicists are finding new uses for models once thought to be nonbiological (Rowlands, 1983), and the process of conducting clinical trials is being challenged by new trends in mathematics and statistics (Couzin, 2004). Moreover, both the successes and the failures of these collaborations can often be traced to their being distributed across several different locations, cultures, institutions, and disciplines (Hastings *et al.*, 2003).

Thus, at the heart of life sciences education reform is the need to teach students from a wide range of disciplines—biology, mathematics, computer science, engineering, physics, chemistry, psychology, medicine, and a host of others—how to work together to solve problems, how to interpret

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the work of scientists in other disciplines, and how to avoid being distracted or dissuaded by the obstacles that may arise in such collaborations. Similarly, students will need to learn how to communicate and interact with students not only from other fields but also from other institutions and organizations, and they will need to learn how to communicate and interact with others via nontraditional tools and technologies that exist in a truly interdisciplinary sense.

For example, mathematicians, physicists, computer scientists, biologists, and health scientists alike will increasingly be asked to work with data in the form of images (Kelley *et al*., 2008). Tools such as video capture and ImageJ (National Institutes of Health, Bethesda, MD) may currently be as unfamiliar to medical personnel as they are to mathematicians, but in the near future they will need to be used as frequently as numerical data in measurement, prediction, and inference (Dougherty, 2009). Similarly, systems biology and computational biology are introducing new approaches for life scientists and new problems for mathematicians, statisticians, and computer scientists that probably would not exist independent of an interdisciplinary context (Allarakhia and Wensley, 2005).

Many interdisciplinary opportunities and outreach efforts have developed in tandem with the need to collaborate—and the need to teach students how to collaborate. However, existing efforts tend to focus on particular aspects of quantitative biology, such as coding or molecular biology. Quantitative biology in general is expected to rely on a broad expanse of collaborations involving a wide variety of scientists; correspondingly, curricular models need to be developed that introduce students to such collaborations. In particular, quantitative biology education will need to develop models in which experimenters, clinicians, and other empirical scientists are involved in collaborations with theorists, model builders, and computational scientists; and these models need to span not only different disciplines but also different institutions requiring an array of different communication tools and collaborative efforts.

Here, we suggest one such model and discuss its implementation. In particular, this article describes the motivation and structure of collaboration between students in a Biomedical Engineering PBL laboratory at Georgia Institute of Technology–Emory Biomedical Engineering program (BME) and students in a senior-level undergraduate mathematical modeling course at East Tennessee State University (ETSU) that was used to investigate an inquiry-based, open-ended problem in physiology (anterior cruciate ligament [ACL] injury differences between male and female athletes). This project was carried out with the support of the Howard Hughes Medical Institute as a part of its science education efforts via existing grants to the two different institutions. Although there is room for improvement on this initial effort (which we discuss in *Assessing Outcomes*), we nonetheless believe this can be used as a model for developing similar multi-institutional collaborations.

COURSE COUPLING AND CASE-BASED LEARNING

The sciences curriculum of the near future is commonly envisioned to be that of an integrated introduction to mathematics, computation, and the sciences in the context of relevant biological problems (Bialek and Botstein, 2004). In particular, there are problems in biology in which temporal, ethical, or spatial considerations require biologists to augment traditional biological approaches with models and techniques from mathematics, statistics, and computation experts (Cohen, 2004). Indeed, some have suggested that the creation of biologically realistic models is foundational to the life sciences of the next century (Bower, 2005).

However, current interactions between biology and mathematics tend to follow from classical interactions over the past 500 yr, especially pedagogically (Cohen, 2004), whereas the types of collaborations driving the quantitative biology revolution tend to be based on relatively recent techniques and models. In particular, the mathematical models introduced in biological contexts, e.g., the predator–prey equations, do not lend themselves to data fitting and testable predictions; likewise, experimental designs in biology tend to focus on the empirical.

Thus, to facilitate the development of models that can be implemented experimentally, the ETSU–BME collaboration used a problem-based learning approach, which is an approach in which students collaboratively develop and implement strategies to solve problems. A particular type of problem-based learning strategy is that of investigative case-based learning (ICBL), in which the problem addressed by the students follows from a case to be investigated, i.e., a problem motivated and defined by a particular example from the real world (Stanley and Waterman, 2005). The case in this project—why female athletes are 4–6 times more likely to suffer ACL injuries than male athletes—emerged from a quantitative biology workshop on case-based learning hosted by Emory University in July 2009 (Pat Marstellar, organizer).

The ACL problem was selected, in part, because such problems in a sufficiently broad context allow courses to be linked in a mutually beneficial manner (Knisley *et al*., 2010). Our goal was to use an ICBL approach with the ACL injury difference problem to couple two courses in two different institutions and disciplines into a coherent case-based learning experience, one that would have model builders creating models that experimenters could implement leading to predictions about the solution to the problem itself. That is, the ETSU–BME project is an experiment in course coupling, in which separate courses with separate pedagogical goals are designed as one meta-course that serves two separate student populations. The course-coupling concept has been used at several institutions, including ETSU and BME, and it serves as a seminal concept in the design and implementation of the Symbiosis Project (Knisley *et al*., 2010).

Once a sufficiently broad yet well-defined problem has been chosen, the next task is that of establishing a timeline for the project. In this project, the timeline was developed to a large degree during the Emory University-hosted workshop, primarily by examining where typical timelines for the individual courses would allow ETSU–BME interaction. The goal was to introduce collaborative activities in association with the project while maintaining the overall structure of the two individual courses. For example, the time period during which the BME students conducted the experiments began a week after the presentations by the ETSU students; thus, this interim week served as a period of dialog during which the project was transferred from the theoretical, model-making activities into the empirical, experimentally design activities.

Another important aspect of this course-coupling experiment was that of at least one face-to-face meeting. Although students in both institutions gravitated toward social networking, e-mail, and cell phones as the primary means of communication, the face-to-face meeting filled both an important social need—that of putting faces with the names—and the important pedagogical need of having the ETSU students transfer the project to the BME students. Although modern communication tools support a host of sophisticated interactions, reflection on the project suggests that the in-person meetings, during which the ETSU students transferred the project to the BME students, were crucial to allowing the BME students to reinterpret the project in a context more familiar to them. Without the in-person spontaneity, many important questions and interpersonal interactions might not have occurred.

Finally, it also seems to be important to create a common website enabling communication and housing a common library of relevant articles and other important materials. In particular, this common library should contain materials explaining the efforts and contexts of one group in terms understandable to the other. For example, for the ACL injury differences project, a library of papers describing experimental equipment, techniques, and expected outcomes was combined with papers describing logistic models and their use.

ETSU–BME COLLABORATION

In fall 2009, ETSU and BME cooperated in an unprecedented curricular experiment. The Institute for Quantitative Biology (IQB) at ETSU coupled a modeling course with a biomedical engineering laboratory at The Wallace H. Coulter Department of Biomedical Engineering, under the direction of one of us (E.B.). The BME lab is a required junior-level course that focuses on experiment design and data analysis. Ill-constrained, problem-based modules are designed to incorporate topics covered in prerequisite lecture-based courses. This collaborative project was the third of a five-module semester. There were 67 undergraduate students enrolled and divided into four sections, with <16 students per section. The modeling course at ETSU is a senior-level course in predictive modeling, in which the emphasis is on data mining via statistical and computational models. The collaborative project occurred during the first month of the course, where the focus is on logistic regression. There were 11 students overall ranging from a particularly talented freshman to a second-year graduate student, with the majority being senior-level math majors and first-year graduate students.

Students in the two courses worked together to address a critical issue in biomedical engineering, that of why females are 4–6 times more likely to suffer ACL injuries than male athletes, and how this difference might provide insight as to why ACL injuries occur so frequently among both genders. The ACL injuries problem was selected because it is current, open-ended, and poorly understood (McLean, 2008). The goal was for the two different populations of students to collaboratively develop insight into possible factors in the ACL injury difference phenomenon that would not have been obtained separately from any other source.

In particular, ETSU mathematics students were required to produce models that could be implemented experimentally; subsequently, Georgia Tech engineering students were required to design experiments that implement the mathematical models and produce data that can be used to estimate parameters in those models. For simplicity, the five models designed by the ETSU students were logit models (logistic regression), because these models are common in undergraduate statistics courses and are a straightforward means of using data to make predictions (Moore *et al.*, 2009). Logistic regression is of the following form: $\mathrm{logit}(p) = w_0 + w_1 x_1 + \ldots + w_n x_n$, where p is the probability of observing an empirical success, $\mathrm{logit}(p)$ is the log-odds of p, the variables x_j are measured in the experiments, and the regression coefficients w_j are estimated using maximum likelihood methods.

In the ACL injury models, the literature suggested that abnormal stress on the ACL results in elevated quadriceps activity, so p is defined to be the probability of significant increase in quadriceps muscle electromyographic activity during a drop-landing. The factors x_j varied from model to model in accordance with the ETSU students' incorporation of biomechanics and ACL-related ideas into their models. Table 1 lists the factors used in the five logistic regression models used in the collaboration.

Table 1. Factors tested experimentally in the five logistic models (all involved drop landings from a height of 50 cm)

Model	Experiment	Factors
1	Variations in feet positions at landing	Duck-foot vs. preferred; trunk, hip, and knee valgus angles at impact, hip–foot ratio, femur–tibia ratio, maximum valgus knee angle, angles of hyperextension, age, gender, previous ACL injury, lifelong athlete
2	Variations in inward flexing of knees at landing	Foot and lower leg flexion angles, valgus flexion angles, ground reaction forces (vertical, posterior), foot area-to-weight ratio, gender, weight, height, effort, previous ACL injury, lifelong athlete
3	Variations in hip rotation at landing	Hip rotation angle, velocity of rotation, weight distribution, ground reaction forces (vertical, posterior), gender, weight, height, previous ACL injury, lifelong athlete
4	Before/after fatiguing exercise	Gender, age, weight, height, fatigue level after exercise, effort, sagittal plane trunk angle, landing center of mass, landing force
5	Fatigue and landing dominant leg first	Gender, age, weight, height, fatigue level after exercise, trunk flexion angle, dominant vs. nondominant leg, landing center of mass, landing force

On September 28, 2009, 10 students from the predictive modeling class traveled to Georgia Tech to present the models to approximately 60 biomedical engineering students. The biomedical engineers subsequently formed teams charged with designing the experiments and collecting the data necessary for model prediction and validation.

Throughout the ACL injury project, students at the two institutions served as consultants for one another. Once the data were collected, they were returned to the ETSU students for analysis, and then the results were shared with the BME students.

The outcomes of the project were modest but respectable. Not all the models lent themselves to implementation, and not all the data from the resulting experiments proved to be analyzable. Many of the models and the resulting experiments focused on fatigue, and although fatigue does seem to be an issue, evidence suggests that it is no more a factor for females than for males. This matches results published previously (Pappas *et al*., 2007).

However, there were several of the BME experimental groups that used the ETSU models to indicate that landing force is significant in predicting ACL injury differences between male and female athletes. Of particular note is that several experiments seem to indicate that as valgus angles increase, male athletes' landing forces tend to decrease, whereas female athletes' landing forces remain the same or increase. That is, although highly preliminary, there is evidence to suggest that males have either a behavioral or physiological means of compensating for the inward bending of their knees by decreasing their landing force. Speculatively, the data may suggest that males tend to use their ankles proactively to protect their knees as they land, whereas females do not.

ASSESSING OUTCOMES

Implementing collaborations across different institutions not only provided a meaningful experience for our respective students but also gave us a chance to assess the development and productivity of the collaborations among two groups of students with no prior interactions. Thus, in addition to the outcomes produced by the collaborations themselves, we assessed the attitudes of the groups individually and the relationships fostered between them. These assessments were then analyzed and summarized to produce a picture of how the students themselves viewed the collaborative experiences.

Initially, at the end of the course, a survey was provided to BME students to gain insight into their experience with the structure of the initial interaction between the students at two universities. In this survey, only 43% of the respondents believed that the initial presentation was important in establishing a collaborative relationship (Table 2). However, when asked how they rated their overall collaboration experience, those who believed that the initial presentations were effective in establishing the collaboration were more than twice as likely to rate their overall collaborative interaction as average or above average, suggesting that this initial meeting was important in their overall experience. Moreover, they were >2 times less likely to state that more interactions would help in establishing a relationship.

Table 2. Student perception (%) of collaborative project[a]

Were the in-person presentations important in establishing a collaborative relationship with ETSU students?		How would you rate the overall collaboration experience with students from ETSU?	
Yes	43	Above average	5
		Average	80
		Below average	15
No	57	Above average	0
		Average	37
		Below average	63

[a] BME student response in the end-of-term voluntary survey to questions relating to collaborative project. Forty-seven students responded to the survey.

Due to the much smaller numbers of student participants at ETSU, the end-of-course survey at ETSU was free response and solicited information not only about the collaborations but also about the results of the collaborations themselves. Of significance is that ETSU students tended to create models with a bias toward what they expected the experiments to show and were surprised when the experiments did not confirm their expectations. In addition, the ETSU students also commented on the tendency of the experimenters to produce data that were not relevant to the models.

However, in agreement with the results from the BME students, the success of the ETSU students' models seemed to be directly connected to the quality of their initial contact with each other and, in fact, the most significant improvement suggested by the ETSU students was that the initial contacts needed to be more focused with fewer students engaged in each such initial meeting. Suggested improvements to this initial meeting by BME students included forming small groups, promoting face-to-face and individual contact, and posting electronic presentations before the initial meeting for better preparation. Moreover, all the data suggest that initial contact was critical to a successful collaboration.

There were collaborations that did produce results, and in these collaborations, the lines of communication established at the initial meeting were invaluable. Indeed, the call for improving the initial contacts seemed to be most significant among those groups that were most productive, and we noted that the most productive collaborations seemed to be those that best used the initial contacts in jump-starting the process of implementing the models themselves. Indeed, groups that did not use the initial contacts to begin implementing the models tended to work somewhat independently of each other after the fact without ever returning to a true collaborative mode.

CONCLUSIONS

A significant challenge in quantitative biology is that of developing productive collaborations that do not have the unrealistic requirement of at least one collaborator being an expert in everyone else's field (Kuczenski *et al*., 2005). Although such collaborations have been developed and have shown to be productive, it is not immediately apparent how students in disparate fields might be taught to collaborate productively even if each member has incomplete knowledge of the field(s) of their fellow collaborators. This project is a first step in addressing how students can be guided into such collaborations, and although admittedly a proof-of-principle more than a complete study, this project shows that such collaborations among students with widely varying backgrounds can be productive.

Moreover, students learn a great deal not only about the associated field but also about how science and engineering will be pursued now and in the future. For example, both the BME and ETSU students learned that although mutual respect is desirable, it is not a substitute for genuine communication. Indeed, the ETSU students did not realize initially that some aspects of their models would be difficult, if not impossible, to implement experimentally; and the BME students did not realize how important a correct interpretation of a theoretical model would be to the experimental design and data collection. Without genuine communication as the ETSU students were handing the project over to the BME students, there may not have been any meaningful results.

That is, the initial efforts in forming collaborations across a variety of disciplines are crucial—so much so that in-person meetings are more than justified—and as importantly, the initial formation of such collaborations should be focused on facilitating approaches and channels of communication that can be used to address a mutual problem (Karsai and Knisley, 2010). Indeed, the need for channels of communication within and between fields is already being addressed by the larger scientific community. For example, scientists are creating a variety of markup languages to facilitate the problem-focused exchange of data and ideas between scientists and practitioners in different fields, including the systems biology markup language (SBML), CellML, and the predictive model markup language (PMML) (Guazzelli *et al*., 2009).

In fact, among the many possible improvements upon this first effort are the incorporation of more avenues and protocols for interaction between ETSU and BME students. For example, a markup language was not used, primarily because it was a first effort, but certainly the use of PMML in particular would have reduced or eliminated the significant workload in translating data and results between the two groups. In addition, the ETSU-BME collaboration would have benefited from a larger library of materials accessible to both groups; likewise, the methods for analyzing data could have been more clearly defined at the outset of the project. And although there was a shared course website within Georgia Tech's course management system, this interactivity could be greatly enhanced. For example, web 2.0, and collaborative tools such as first class, blogs, wikis, or other meeting tools would have greatly enhanced this first effort.

Nonetheless, this first attempt was quite successful and illustrates how students from different disciplines and institutions can collaborate and even instruct one another while addressing an important problem in quantitative biomedicine. Moreover, the experience was mutually beneficial, providing insight to the modeling course that could not have been obtained otherwise and introducing engineering students to the concept of implementing and using theory rather than just seeing it in a textbook. Indeed, we feel that this project serves as a model for introducing students to the important need to communicate and collaborate across disciplines, organizations, and even institutions.

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