

Board 11: Predicting At-Risk Students in a Circuit Analysis Course Using Supervised Machine Learning

Prof. James P Becker, Montana State University

James Becker is a professor of electrical and computer engineering at Montana State University. His professional interests include microwave circuits, radio frequency electronics, nanoelectronics, cyber-learning, metacognition, and distance education.

Ms. Emily Sior, Montana State University

Emily Sior is a student at Montana State University, graduating in May 2019 with a major in Electrical Engineering and a minor in Computer Engineering. Her interests include software development and database integration.

Mr. Jerad Hoy, Montana State University

Dr. Indika Kahanda, Montana State University

Dr. Indika Kahanda is an Assistant Professor in the Gianforte School of Computing at Montana State University. His research interests include Bioinformatics and Biomedical Natural Language Processing. He works on the application of machine learning, data mining and natural language processing techniques for solving problems related to large-scale biological data. His current work focuses on predicting mental illness categories for biomedical literature, protein function prediction and protein-function relation extraction from biomedical literature. He received his Ph.D. in Computer Science from Colorado State University in 2016 in the area of Bioinformatics, a Master of Science in Computer Engineering from Purdue University in 2010, and a Bachelor of Science in Computer Engineering from University of Peradeniya, Sri Lanka in 2007.

Predicting At-Risk Students in a Circuit Analysis Course Using Supervised Machine Learning

Abstract

Writing exercises may be used in problem-centric STEM-based courses to identify common misconceptions held by the writer as well as to probe their metacognitive processes. As grading of writing samples and providing personalized feedback regarding a student's writing can be time-intensive, opportunities to automate the process while retaining the integrity of the grading and quality of the feedback are attractive.

This paper describes the motivation and use of a writing-based exercise in a sophomore-level course on electric circuit analysis. The conversion of a paper-based writing exercise to a web-based application is detailed as is its initial use in this new format. The ultimate goal of implementing a web-based approach to administering the writing exercise is to build a fully automated application capable of evaluating student responses and providing feedback to the user in an attempt to enhance their conceptual understanding of challenging material in a manner that acknowledges instructor workload in high-enrollment, resource-constrained courses.

The first element in the planned automated evaluation aspect of the writing application is the identification of students scoring at the lowest end of a holistic scale. This is of significant value as there is evidence that such students are at-risk to fail the electric circuits course as it is currently constructed. Use of a basic natural language processing (NLP) pipeline on a dataset of more than one hundred student responses is described as are the initial results of the at-risk / not at-risk binary classification task.

Introduction

Student struggles in gateway STEM courses such as electric circuit analysis are common. A review of the literature points to at least two important factors that help explain such struggles even among students seemingly engaged in such a course. One factor arises due to the abstract nature of the physical phenomenon underlying the behavior of electric circuits. In a typical electric circuits course, students take macroscopic measurements of voltage and current in the lab as well as calculate these quantities in a variety of circuits. The macroscopic quantities result from the microscopic behavior of electrons in the circuit and this microscopic behavior is not often discussed in a standard course on electric circuits nor described in most textbooks used in such courses. The literature identifies a number of common misconceptions of students entering a first course on circuit analysis [1]-[7]; many of these misconceptions arise from a lack of understanding of certain microscopic details and some are particularly "robust" [8] and thus difficult to correct. Examples of common misconceptions found among students studying circuit analysis include belief that current is consumed, that the "flow" of current is a sequential process, and that batteries are sources of constant current. Even some popular textbooks may support such misconceptions through use of inconsistent models and analogies [4]-[6]. Various efforts to help foster deeper, more conceptually accurate knowledge of electrical circuits have been investigated and shown to be beneficial, for example [7], [9], and [10].

A second reason that students may struggle in gateway STEM courses in general, and in electric circuit analysis in particular, has to do with a student's lack of self-regulated learning skills. What are the traits of an ideal learner? The ideal learner, as described in [11], "would self-regulate their learning by identifying their own knowledge deficits, detecting contradictions, asking good questions that rectify these anomalies, searching knowledge sources for answers, making inferences when answers are not directly available, and actively building knowledge at deep levels of mastery." Self-regulated learning emerges from skilled metacognition.

The foundation of much of our current understanding of metacognition may be traced to Flavell. In an early paper [12] of Flavell, he notes, "In any kind of cognitive transaction with the human or non-human environment, a variety of information processing activities may go on. Metacognition refers, among other things, to the active monitoring and consequent regulation and orchestration of these processes in relation to the cognitive objects or data on which they bear, usually in service of some concrete goal or objective." As stated by Pintrich [13], "Although there are many definitions and models of metacognition, an important distinction is one between (a) knowledge of cognition and (b) the processes involving the monitoring, control and regulation of cognition." Often students in gateway STEM courses demonstrate poor knowledge of cognition as they, "confuse their ability to recognize vocabulary with mastery of material" [14] and thus clearly are unaware of their knowledge deficits.

In courses such as electric circuit analysis that emphasize problem solving resulting in definitive numerical answers, it is easy for students to "hide" their lack of understanding in a multitude of formulas. Within mathematics, the use of writing has been shown to be a powerful alternative as,

written products provide a rich and extensive view of the mathematics that students know and their capabilities in applying that knowledge. Such assessment measures provide substantially more information than traditional measures, which frequently focus on the correctness of a single answer or response. Through writing, students record their thinking. Their products become a window into their cognitive processing while they are engaged in mathematical tasks [15].

Why then is writing not more commonly used in STEM problem-centric courses? It must be acknowledged that, "*the assessment of these written products can be daunting*" [15].

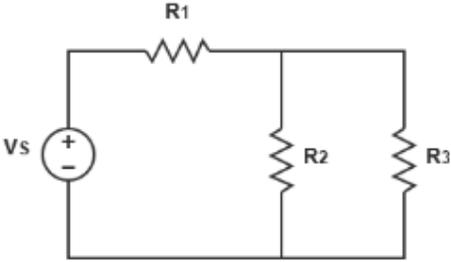
On the fifth class period of EELE 201– Circuits I at Montana State University during the fall 2017 semester, a writing-based exercise was administered. As described in detail in [16], the writing exercise was graded on a holistic 1-5 scale in which not only the correctness, but the richness of the response in terms of supporting evidence and demonstration of metacognitive activity was considered. Results from this pilot effort suggested that the delineation between those scoring a 1 (the lowest level) and those scoring from 2-5, appeared to serve as a meaningful separation between those at-risk for failing the course and those likely to go on to succeed in the course. In the next section, the conversion of this paper-based written exercise to a web-based application is described. While the ultimate goal is to create a fully-automated web-based application that not only collects student responses, but also evaluates them and provides meaningful feedback to the

user, at this point the web-application only collects the responses and a post-processing routine has been investigated to automatically identify at-risk students.

Conversion of the Paper-Based Writing Exercise to a Web-based Application

Shown in Figures 1 and 2 are images of a web-based version of the original writing exercise described in [16]; the application was developed using html, css, and javascript. The writing application is functional in terms of accepting and storing various data. The image shown in Figure 1 is that which appears immediately after the login screen. As suggested in Figure 1, prior to answering the primary question, students rate their perceived understanding of the question and ability to meaningfully answer it. They will perform the same ratings after completing their response to the main question, thus allowing for a pre- and post-quiz comparison, yielding insight into a student's metacognitive awareness (i.e. knowledge of cognition). After providing their ratings via the screen shown in Figure 1, the student is presented with the main question screen as shown in Figure 2.

Consider the circuit shown below and assume that the elements are ideal. Explain what happens to the power associated with V_S , R_1 , R_2 , and R_3 as the resistance of R_2 decreases while the other component values (V_S , R_1 , and R_3) remain unchanged. Thoroughly explain the rationale supporting your conclusions, using equations only as necessary. Write in complete sentences.



It is your thought process that is the most important, so write what you are thinking and respond to all prompts given. You will have approximately fifteen minutes to complete the problem.

(1) Rate your perceived understanding of the question in which a rating of 100% means you completely understand the question. Enter the percentage in the box below.

%

(2) Rate your perceived ability to meaningfully answer the question in which a rating of 100% indicates you are certain you will be able to meaningfully answer the question. Enter the percentage in the box below.

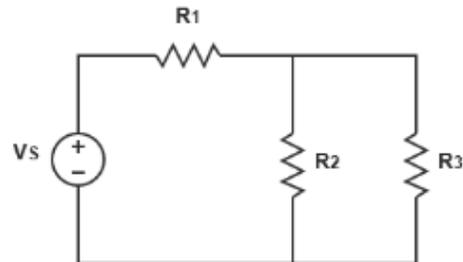
%

Figure 1: An image from a web-based version of the original writing exercise described in [16].

Consider the circuit shown below and assume that the elements are ideal. *Explain what happens to the power associated with V_S , R_1 , R_2 , and R_3 as the resistance of R_2 decreases while the other component values (V_S , R_1 , and R_3) remain unchanged.* Thoroughly explain the rationale supporting your conclusions, using equations only as necessary. Write in complete sentences.

Complicated formulas are not desired. If an equation is necessary, please build it into a complete sentence with the help of the buttons below.

the equation	equals
multiplied by	divided by
squared	greater than
less than	current
voltage	power



To summarize, your response supports the following conclusions as the resistance of R_2 decreases:

- The power associated with V_S :
- The power associated with R_1 :
- The power associated with R_2 :
- The power associated with R_3 :

Figure 2: An image of the main problem page from the writing application. The text field where students enter their responses has been greatly reduced from the default size to facilitate presentation of the entire page in the figure.

Several notable changes have been made in transforming the writing exercise from how it is described in [16] to its web-based counterpart. In the original writing exercise, after reflecting and reporting on their perceived understanding of the question and ability to answer it, students were presented with the following question: “How will you start the problem and what prior knowledge do you have to answer the question?” The initial self-ratings and subsequent question regarding starting the problem were intended to trigger metacognitive activity and can be considered to encompass the first three phases of Polya’s [17] process of solving mathematical problems.

In composing the web-based version of the writing exercise, while the self-rating questions have been retained, the question asking how the student would begin to answer the exercise's primary question and what relevant prior knowledge they possess has been eliminated. When administered as a handwritten exercise, it was noticed in a significant number of cases that the student would either direct the reader back to this portion of the quiz when answering the main question, or would, when answering the main question, continue to write about how they planned to solve the problem and never directly address the primary question. For these reasons, and to better focus students to the main task, this question has been eliminated.

As a measure to remind students that they are to explain what happens to the power of *each* of the four elements, the student must indicate via a drop-down selection what their response supports regarding the power in a given element (see Figure 2). The drop-down allows a student to select either increases, decreases, or remains the same. This measure was proposed as many students were found to give an incomplete response to the main question, perhaps only definitively responding regarding the power of one or two of the elements. It should be noted that the default size of the text box in which a student responds to the primary question is much larger than suggested in Figure 2 – the box was reduced in size to facilitate displaying the entire screen in the figure. To keep students focused on the task, should a student go thirty seconds without typing in the text field, he or she is reminded via a pop-up that it is their thinking process that is most important and thus encouraged to resume responding.

Another important change made in converting the writing-based exercise to a web application is the addition of the text buttons suggested to the left of the circuit in Figure 2. In evaluating the hand-written exercises, many students were found to use formulas that were poorly formatted and strewn across the page. As the ultimate goal is to have a computer algorithm evaluate and provide feedback based on the user's response, it is important that the input to the algorithm be of a more consistent form than often found in the handwritten work of students. Both the buttons that encourage a particular formatting of equations using words and not symbols, and through reminding students of what they are truly supposed to respond to via the required drop-down selection options depicted in Figure 2, it is expected that implementing a suitable algorithm to evaluate the writing will be facilitated.

As fostering active metacognition is desired, in particular regulation of cognition, after a student submits their responses to the questions posed in the image of Figure 2, he/she is required to submit their final confidence scores, asked to review their response to the main question, and to reply to the following questions:

1. *Identify the sentence from your response with which you have the least confidence and explain why you question its accuracy.*
2. *Identify the sentence from your response with which you have the most confidence and explain why you are convinced of its accuracy.*

In addition to the self-ratings and questions just described, the writing application monitors the total time a user takes to complete the exercise and the number of times the "continue writing" pop-up triggers. Initial testing of the web-based writing application in EELE 201 took place on the fifth day of the spring 2019 semester.

Comparison of Hand Written and Web-Entered Responses

As described in [16], results from its initial use suggest that the paper version of the writing exercise may be a valuable means to identify students at-risk for failing the specific circuits course in question. For example, of the fifteen students scoring a one (the lowest score on the one-to-five scale) on the writing exercise, fourteen scored 70% or below on the first exam, eight of whom scored below 60%. This is particularly notable as previous analysis has identified Exam 1 as a key indicator of student success in the course overall [18]. Since the writing exercise was administered on the fifth day of class, such information is available early enough in the semester to direct the student to the appropriate resources. It is instructive to consider whether there are significant differences in student responses to the main question depending on whether the writing exercise was given in paper form or via the web-based application. Table 1 collects several comparisons between when the exercise was administered in paper form (Fall 2017 and Fall 2018) and when it was delivered via web-based application (Spring 2019). The typical enrollment in the circuits course during spring semesters is often less than half of that in fall semester

Table 1: Comparison of Student Responses in Hand-Written Versus Web-Based Delivery

Delivery Method	Mean number of sentences	Mean Number of Equations	Mean number of elements addressed
Hand Written (F17, n = 69)	4.16	3.55	2.24
Hand Written (F18 n = 62)	4.26	3.15	2.16
Web-Based (SP19 n = 28)	5.00	1.35	2.85

In light of the modest sample size ($n = 28$) during the spring 2019 semester in which the web-based application debuted, any conclusions drawn from the data of Table 1 should be considered preliminary. With that caveat noted, it does appear that the web-based approach may have indeed been successful in encouraging students to respond regarding the power of each of the four elements, and to do so using text rather than falling back on a string of equations. To be considered an equation, either a formula such as $V=IR$ would be given or it could be written out as voltage equals current times resistance. Simply saying, "by Ohm's Law," would not be considered using an equation. The fourth column of Table 1 provides the mean number of elements addressed. As the question asks the student to address the power in each of the circuit's four elements, the maximum value is four. To be counted in the average of the fourth column, the response had to include some rationale, correct or incorrect, as to whether the power of a given element increases, decreases, or remained the same as the resistance of R_2 decreases.

While various optical character recognition methods could be used to convert handwritten work to a text file for processing via natural language processing algorithm, the extra step of scanning the text and submitting it to the evaluation algorithm eliminates the most important feature of the web-based application under development, namely immediate feedback. Furthermore, as suggested by the data given in Table 1, the web-based format appears to encourage students to more closely respond to the exercise's main question and to do so without resorting to a litany of equations, though certainly additional study is necessary to verify the initial findings.

Binary Classification of At-Risk Versus Not At-Risk Students

An initial inquiry into classifying an existing labeled dataset that consists of over one hundred student responses to the primary question posed in the exercise as suggested in the screenshot of Figure 2 has been completed. As the web-based application has only recently been developed, all responses in the original dataset were handwritten and followed the question as described in [16]. An important point to make is that in transcribing the responses for evaluation by computer algorithm, in many cases the response had to be assembled from text and equations strewn across the paper. The rubric used by the human graders did not penalize for a poorly formatted response as long as the meaning was clear to the evaluator. The existence of such a variety in formatting by students underscores the importance of the “normalizing” features (equation buttons and drop-down summary answers) of the web-based application described previously.

The goal of this preliminary study was to determine how a basic Natural Language Processing (NLP) approach, bag-of-words (BOW) features with a supervised learning model [19], would fair in a binary classification task aimed at separating students with a score of one versus those scoring above a one. That is, we investigated how effective a simple statistical NLP pipeline would be in correctly predicting at-risk students. Why is this a valuable question to answer? Let’s imagine that students answered the question within the web-based application and immediately after submission, and without need of grading the quizzes by hand, the instructor is presented with a list of students predicted as at-risk to fail the course. As such a quiz has been administered on the fifth day of class, at-risk students could be directed to assistance early enough in the course to make a difference.

BOW is a statistical approach to representing text in which documents are modeled with a vector containing a collection of their constituent “tokens” (e.g. words, punctuation marks, symbols, etc.). Creating such a vector is done through “tokenizing.” Tokenization can be more than simply separating words by the spaces or punctuation in the original document and may invoke stemming and/or lemmatization [20]. We employed the Python-based NLP package, spaCy [21] and machine learning package, scikit-learn [22] using a stratified three-fold cross validation approach [20]. As this was the first attempt to classify student responses through NLP, stemming and lemmatization were not applied. So-called *stop words* such as ‘a’, ‘an’, ‘the’, ‘of’, etc. were removed as such words typically carry little information about the text and so increase the vocabulary size unnecessarily. In one analysis only unigrams were considered, meaning that the order of words was not considered. Omitting stop words reduced the vocabulary size (i.e. number of unique words across all documents) to 489 in this case. In a second analysis, both unigrams and bigrams (two words in succession) were considered and as before, stop words were removed. Considering both unigrams and bigrams increased the vocabulary size to 2636. It should also be noted that the default settings of spaCy and scikit-learn were used and so no parameter tuning was pursued. While only a simple NLP pipeline was employed, and done so without optimization, the results of this study are promising as suggested in Table 2.

As quoted in Table 2, the class label distribution of the corpus considered in the analysis consisted of 22 responses scoring a one by human evaluation (labeled *positive* for at-risk) versus 95 being scored above a one through human evaluation (labeled *negative*); the responses are from Fall 2017 and Fall 2018. Due to the class imbalance in the dataset (22 in the at-risk class versus 95 in the not at-risk class) *balanced accuracy* is given. In the case of only unigrams, the balanced accuracy

is 82%; when considering both unigrams and bigrams, the balanced accuracy increases to 86%. The *precision* of our rudimentary NLP classifier, the fraction of correct predictions of the at-risk class over the number of instances in which the classifier identified a response as in the at-risk class, was found to be approximately 79% when considering only unigrams, and 83% if bigrams were included in the analysis. The *recall* of the classifier was found to be approximately 72% in the unigram-only case and 77% when bigrams were included. In this case, recall can be understood as the fraction of accurate predictions of the at-risk class over the total number of samples that were in the at-risk class as determined by human evaluation. Both precision and recall are important to consider as depending on the application, one might be more interested in optimizing one over of the other. In our case of identifying at-risk students, it would likely be preferred that we catch all the at-risk students at the expense of misclassifying a few not at-risk students – thus we would seek to optimize recall. Whether the application calls for optimizing recall or precision, this may be achieved through adjusting the classification threshold within the NLP pipeline.

**Table 2: Summary of Binary Classification Study
Using A Basic Bag-of-Words Approach with Default Settings**

Unigrams (Vocabulary Size = 489)				
Class distribution	Balanced Accuracy	Precision	Recall	AUROC
95 versus 22	0.82	0.79	0.72	0.96
Unigrams and Bigrams (Vocabulary Size = 2636)				
Class distribution	Balanced Accuracy	Precision	Recall	AUROC
95 versus 22	0.86	0.83	0.77	0.96

Just as the precision and recall are quite good in our simple NLP pipeline’s binary classification, so is the AUROC (area under the receiver operator characteristic) score [23]. In the current case, the AUROC score can be interpreted as the probability that a randomly chosen response that is in the at-risk group is more likely to be classified as at-risk than a randomly chosen not at-risk response. *Again, it should be emphasized that the results in Tables 1 represent those obtained using a very basic NLP pipeline with no parameter tuning.* It is reasonable then that through parameter tuning and careful selection of the classification threshold, the system could be optimized to identify at-risk students in terms of their score on the example writing exercise.

The primary motivation for moving towards a web-based writing application is to develop a mechanism whereby students receive *instantaneous* feedback regarding their conceptual understanding of challenging course material as illuminated through their writing and not simply based on a correct or incorrect value as calculated through an equation, or through a multiple choice exam such as that of Engelhardt and Beichner [1]. As many gateway STEM courses have high enrollments, the amount of time on the part of the instructor to promptly evaluate and provide feedback on the handwritten work of students discourages the use of writing in this manner at all.

While the Bag of Words (BOW) approach described above could be extended to a multinomial classification routine to separate writing samples into separate bins of one through five to correspond with what was completed with a rubric via human evaluation, this does not solve the issue of providing feedback. The challenges in realizing the automated evaluation of short answers within a specialized domain such as electric circuit analysis are different than those in conventional essays.

Much of the work of an automated scoring engine for essays can be done at the levels of spelling, grammar, and vocabulary, whereas an engine for short answers must address meaning as a primary concern. From the perspective of computational linguistics, an essay scoring engine is primarily, but not exclusively, an application of computational syntax and stylistics, while a short answer scoring engine is primarily an application of computational semantics. The former fields have the more mature technology [25].

A particularly promising means of carrying out the semantic analysis required to ultimately provide automatic feedback to students based on their typed responses is to utilize a fuzzy sentence matching approach within a rule-based NLP algorithm [26]. Rule-based approaches are particularly effective at parsing and extracting key information at the sentence level. Rules can grow over time to enhance performance without significant changes to the core system. In contrast to many statistical approaches, deficiencies in an existing rule-based system are easily understood as the rules are assembled by the system developer. Furthermore, a rule-based approach does not require a massive training corpus to “understand” user responses. The primary downside of this approach is that a domain expert is needed to compose meaningful rules. Extending the web-based writing exercise in the manner is planned.

Conclusions

A web-based approach to implementing a writing exercise in a course on electric circuit analysis has been described. Results from a previous study suggest that a similar writing exercise administered on day five of a specific course on electric circuit analysis could serve as a tool to identify students at-risk to fail the course. A Bag of-Words approach to analyzing student responses suggests the binary classification of at-risk versus not at-risk may be done effectively via a computer algorithm instead of through human evaluation of student responses. Therefore, a web-based application that not only accepted and stored student responses automatically, but also implemented this binary classification pipeline could be used, with minimal instructor effort, to identify students likely to struggle in course. This is of particular value in high-enrollment gateway courses with limited resources. While employing a writing exercise for such a purpose could indeed be useful, the primary value of implementing writing exercises in a problem-centric STEM course is to draw students beyond simply memorizing formulas, in favor of thinking more deeply about concepts in the course and more critically evaluating their understanding of these foundational concepts. Toward this end, effort is now being directed toward introducing additional writing exercises in the electric circuit analysis course in question. Such writing exercises are to become a tool for enhancing both student understanding and their metacognitive skill rather than simply a means to identify those likely to struggle in the course.

Acknowledgements

The authors would like to acknowledge the support of the National Science Foundation through Grant 1504880.

Works Cited

[1] Paula Vetter Engelhardt and Robert J. Beichner, “Students’ Understanding of Direct Current Resistive Electrical Circuits,” *American Journal of Physics*, Vol. 72 (98), pp. 98-115, 2004.

- [2] Tatiana V. Goris and Michael J. Dyrenfurth, "How Electrical Engineering Technology Students Understand Concepts of Electricity. Comparison of Misconceptions of Freshmen, Sophomores, and Seniors," Proceedings of the 2013 American Society for Engineering Education Annual Conference and Exposition. Paper ID 5849.
- [3] David P. Tallant, "A Review of Misconceptions of Electricity and Electrical Circuits," The Proceedings of the Third International Seminar on Misconceptions and Educational Strategies in Science and Mathematics, August 1-4, 1993.
- [4] Deepika Sangam and Brent K. Jesiek, "Conceptual Understanding of Resistive Electric Circuits Among First-Year Engineering Students," Proceedings of the 2012 American Society for Engineering Education Annual Conference and Exposition.
- [5] Richard Gunstone, Brian McKittrick, Pamela Mulhall, "Textbooks and their authors: another perspective on the difficulties of teaching and learning electricity," in *Research and the Quality of Science Education*, Kerst Boersma, Martin Goedhart, Onno de Jong, Harrie Eijkelhof, eds. Springer, 2005.
- [6] Deepika Sangam and Brent K. Jesiek, "Conceptual Gaps in Circuits Textbooks: A Comparative Study," IEEE Transactions on Education, Vol. 58, August 2015, pp. 194-202.
- [7] Brian J Skromme, "Addressing Barriers to Learning in Linear Circuit Analysis," 122nd ASEE Annual Conference and Exposition, Paper ID #14125, June 2015.
- [8] Michelene T.H. Chi, "Commonsense Conceptions of Emergent Processes: Why Some Misconceptions Are Robust," Journal of the Learning Sciences, 14(2), pp. 161-199, 2005.
- [9] James P. Becker, Carolyn Plumb and Richard Revia, "Project Circuits in a Basic Electric Circuits Course," IEEE Transactions on Education, Vol. 57, No. 2, pp. 75-82, May 2014.
- [10] A. Yadav et al., "Problem-based learning: Influence on student's learning in an electrical engineering course," J. Eng. Educ., vol. 100, no. 2, pp. 253-280, Apr. 2011.
- [11] Arthur C. Graesser, Sidney D'Mello and Natalie Person, "Meta-knowledge in Tutoring," in Handbook of Metacognition in Education, Douglas J. Hacker, John Dunlosky and Arthur C. Graesser, eds., Routledge, New York, 2009.
- [12] John Flavell, "Metacognitive Aspects of Problem Solving," in The Nature of Intelligence, Lauren B. Resnick ed., Lawrence Erlbaum Associates, Hillsdale, N.J., 1976.
- [13] Paul R. Pintrich, "The Role of Metacognitive Knowledge in Learning, Teaching, and Assessing," Theory Into Practice, Vol. 41, No. 4, pp. 219-225, 2002.
- [14] Julie Dangremond Stanton, Yyanthe N. Neider, Isaura J. Gallegos, and Nicole C. Clark, "Differences in Metacognitive Regulation in Introductory Biology Students: When Prompts Are Not Enough," CBE – Life Science Education, Vol. 14, 1-12, Summer 2015.

- [15] *Writing to Develop Mathematical Understanding*, David K. Pugalee, Christopher-Gordon Publishers, Inc. Norwood, Massachusetts, p. 111, 2005.
- [16] James P. Becker and Carolyn Plumb, “Identifying At-Risk Students in a Basic Electric Circuits Course Using Instruments to Probe Students’ Conceptual Understanding” ASEE Annual Conference and Exposition, Paper ID #21478, June 2018.
- [17] *How To Solve It – A New Aspect of Mathematical Method*, George Polya, New Princeton Science Library Edition, Princeton University Press, Princeton, NJ. 2014.
- [18] James P. Becker and Carolyn Plumb, “Towards a Web-Based Homework System for Promoting Success of At-Risk Students in a Basic Electric Circuits Course” ASEE Annual Conference and Exposition, Paper ID #18494, June 2017.
- [19] *Machine Learning*, Tom M. Mitchell, McGraw-Hill Science, 1997.
- [20] *Natural Language Processing in Action*, Hobson Lab, Cole Howard, and Hannes Hapke, Manning Publications, 2018.
- [21] *Applied Text Analysis with Python: Enabling Language-Aware Data Products with Machine Learning*, Benjamin Bengfort, Rebecca Bilbro and Tony Ojeda, O’Reilly Media, Inc. 2018.
- [22] Fabian Pedregosa et. al. “Scikit-learn: Machine Learning in Python, Journal of Machine Learning Research,” Volume 12, 2011.
- [23] Viv Bewick, Liz Cheek, and Jonathan Ball, “Statistics review 13: Receiver operating characteristic curves,” *Critical Care*, Vol. 8, No. 6, December 2004.
- [24] Paula Vetter Engelhardt and Robert J. Beichner, “Students’ Understanding of Direct Current Resistive Electrical Circuits,” *American Journal of Physics*, Vol. 72 (98), pp. 98-115, 2004.
- [25] Chris Brew and Claudia Leacock, “Automated Short Answer Scoring Principles and Prospects”, in *Handbook of Automated Essay Evaluation – Current Applications and New Directions*, p. 136, Routledge, New York, 2013.
- [26] *Machine Learning*, Tom M. Mitchell, McGraw-Hill Science, 1997.