Tracking Evidence of 'Complex Epistemic Performance' in Online Learning Environments: The Case of Critical Clinical Thinking

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This brief report updates work-in-progress in a cross-disciplinary project involving a University of Illinois team from Veterinary Medicine, Medicine, Computer Science and Education, supported by a grant from the Illinois Learning Science Design Initiative (ILSDI). Trials are still underway, with further data still to be analyzed. A National Science Foundation research application is nearing completion.

1. Project Aims

Medical education has long been criticized for its view of science-as-fact and didactic pedagogies that emphasize memory of universally applicable fact and theory (Benner, Hughes, and Sutphen 2008; Gambrill 2012). Mukherjee (2015) recounts his medical education in the following way: "The profusion of facts obscured a deeper and more significant problem: the reconciliation between knowledge (certain, fixed, perfect, concrete) and clinical wisdom (uncertain, fluid, imperfect, abstract)." Teaching case analysis is often delayed in medical curricula, and moved to clinical settings where there is limited systematic documentation on the part of the clinician, and little or no structured analysis of critical clinical thinking processes (Ferguson, McNeil, Schaeffer, and Mills 2016 Forthcoming). The general problem addressed by this project has been how to teach and assess 'complex epistemic performance' such as critical thinking that weighs up alternatives, and problem solving that is context- and case-sensitive. Our solution uses the *Scholar* platform developed by U of I researchers to support multimodal knowledge representation and structured peer feedback, focusing on critical disciplinary practices and metacognitive strategies. We have also been exploring computational and assessment possibilities, both around structured peer review and instructor data, supplemented by computational approaches that mine unstructured or semi-structured data emerging through all stages of the learning process (Cope and Kalantzis 2015b).

None of the available assessment technology clusters—principally item-based testing, intelligent tutors, and text grading using natural language processing—is particularly well calibrated to the learning and assessment of 'complex epistemic performance' (Cope and Kalantzis 2015a;

Cope, Kalantzis, McCarthey, Vojak, and Kline 2011). This reflects a more general challenge across all STEM disciplines, and across all levels of learning, from upper elementary to higher education (Cope, Kalantzis, Abd-El-Khalick, and Bagley 2013). The *Scholar* platform has been developed to address this challenge from an infrastructure perspective; our vision is to extend it with advanced computational methods, particularly those in intelligent information retrieval, text mining, and machine learning for automated assessment and large-scale learning analytics.

Although the learning and assessment technologies upon which we have been working are specifically for clinical case analysis in medical and veterinary education, the platform and algorithms for analyzing critical thinking that we have been developing, and whose further development we now propose, will be widely applicable.

Our premise in this project is that certain forms of scientific thinking and practice are most effectively represented and communicated in extended, written documentation. For this project, the documentation is of clinical cases. We define as 'extended', texts that have multiple paragraphs, and which, when writing on a computer, at times may also contain embedded media such as diagrams, tables, photographs, videos, audio files, datasets and hyperlinks. We call these 'multimodal' texts (Kalantzis and Cope 2012). Beyond medical cases, and in the larger domain of STEM education and across a wide range of learning levels, other examples of such texts to which our technologies might be addressed include a report of lab-based experiment, an argument using scientific reasoning to make a case for a certain course of action in support of community sustainability, a report of a project-based engineering activity, or a proposal for the design and implementation of a new technology. Our key operational concepts are 'representation' (making meaning for oneself—in this case, multimodal writing as a tool for science-based reasoning), and 'communication' (scientific communication that offers assessable evidence of scientific learning) (Cope and Kalantzis 1993; Kalantzis and Cope 2012). These processes of representation and communication constitute the 'disciplinary practice' of science and media for 'complex epistemic performance' that underlie representation and communication of science knowledge (Gee 2004; Halliday and Martin 1993; Lemke 2004).

In the *Scholar* prototype used in this project's trial, the process of critical clinical thinking goes through a number of phases:

- *Phase 1: Drafting the clinical case.* Students plan and write up their case in *Scholar's* multimodal editor. Media that can be embedded online include image, diagram, video, dataset in any format, mathematical notation, and externally located web media. As they draft on the left panel in the screen, they view on the right of the screen, the critical clinical thinking rubric designed by the instructor for this case (Fig.1 - See Appendix).

- *Phase 2: Peer feedback.* Students review others' critical clinical case analyses (in the case illustrate here, 3 texts, anonymous review). These are different cases, but use the same criteria to review these cases as they had available to them as they wrote their own. Students also offer detailed commentary with in-text annotations.
- *Phase 3: Revision.* Students receive their peer feedback and annotations (in this case, 3 sets of feedback and annotations), and optionally also instructor feedback, in order to revise their text (Figs 2 and 3). They revise their work, based on this feedback. They write a self-review, again against the rubric, accounting for describing the revisions they have made to their work based on the feedback received, which feedback they have found valid and applied (or not), and rating/reviewing the reviewer on each criterion.
- *Phase 4: Publication.* Instructors provide further feedback to students and can post case analyses to student e-portfolios as well as the class 'community' for wider analysis and discuss. At this stage, further revision is possible.

Instructors have access at all stages during the project to a learning analytics dashboard representing a wide range of data perspectives including peer, instructor and self review scores, the amount of revision undertaken between versions, the number and length of reviews offered, the number of annotations and an overall score. Below we describe two pilot courses on teaching critical thinking that were taught on *Scholar* with support from ILSDI, one for first-year veterinary students and one for first-year medical students.

2. Fostering Critical Thinking Amongst First-Year Veterinary Students

The *Scholar* platform was used to conduct student clinical case analyses in the first quarter of instruction of the UIUC veterinary school, with cases focusing upon endocrine physiology. These analyses were conducted over the last 2 weeks of the 8 week integrated course as part of "Clinical Correlations." Each student was assigned one of the 4 following cases to analyze, but were not provided the diagnosis:

1. Adult dog with diabetes mellitus
2. Cow with postpartum hypocalcemia ("Milk fever")
3. Puppies with panhypopituitarism (pituitary dwarfism)
4. Adult dog with Addison's disease (hypoadrenocorticism)

The case scenarios with guiding questions were presented in the *Scholar* "community." All 4 cases were available to all students. The students were given guiding questions as a scaffold for their analysis, including the request that they reflect on at least 2 learning issues they had with the case, and that they provide references for their work. Then, after submitting first drafts of the analyses after 7 days, each student was assigned 3 other analyses to peer-review with each of the other cases being represented. After this peer review period of 4 days, students were given 4 days to revise their first draft using comments from the reviews. After the final revisions were completed, Dr. Ferguson reviewed the analyses with the same rubric. The 6 criteria of the rubric category are listed below, and students were score on a 5-point scale: Novice, Advanced Beginner, Competent, Proficient, and Expert.

1. Problem List Analysis
2. Evidence of Appropriate Information/Literature Search
3. Judgment of Quality of Information
4. Analysis of an Argument
5. Clarity of Communication
6. Understanding of Connection to Content (physiology, anatomy, neurobiology and/or histology)

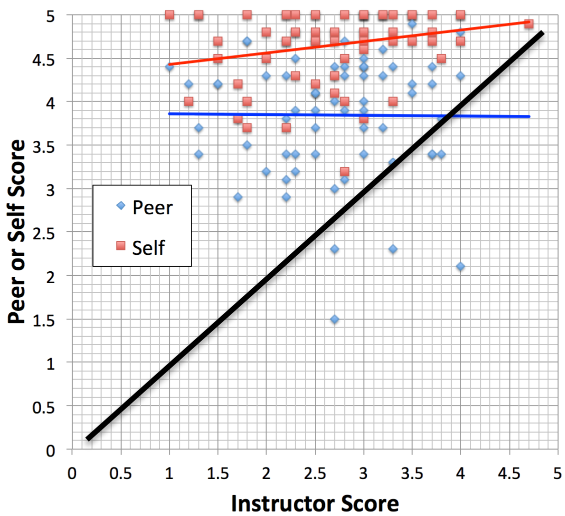
Observations

The *Scholar* Analytics dashboard below shows a subset of the case analysis data. The average peer review score (5th column) can be compared with the student's self-review (6th column) and the instructor ("Publisher) (7th column) reviews. Some subjective observations were that students, with a few exceptions, took the peer-review process seriously (see average review length and number of annotations in analyzed document (10th and 11th columns). In addition, the authors undertook significant editing following peer review (3rd column). The general observation was that the student analyses were generally of high quality for the stage of their career, averaging from "Advanced Beginner" to Competent."

Num Vers	Avg Ver Len	Avg Ver % Edited	Academic Lang Lvl	Avg Peer Rev Rating (Num)	Avg Self Rev Rating (Num)	Avg Pub Rev Rating (Num)	Avg Overall Rev Rating (Num)	Num Rev Auth	Avg Rev Auth Len	Num Annots	Overall Score %
3	1,024	35.7	11.7	1.5/5 (3)	--	2.7/5 (1)	1.8/5 (4)	3	136	14	75.3
3	1,504	28.4	12.7	3.3/5 (3)	4.7/5 (1)	3.3/5 (1)	3.6/5 (5)	3	495	10	87.3
4	1,030	6.3	8.3	4.0/5 (3)	4.3/5 (1)	2.7/5 (1)	3.8/5 (5)	4	271	15	87.0
3	987	14.4	12.4	4.4/5 (3)	5.0/5 (1)	--	4.6/5 (4)	3	152	7	93.9
5	1,192	10.6	9.9	4.8/5 (3)	5.0/5 (1)	4.0/5 (1)	4.7/5 (5)	4	338	9	94.4
4	1,113	24.4	10.3	3.3/5 (3)	4.0/5 (1)	3.3/5 (1)	3.4/5 (5)	4	166	6	86.2
3	1,241	21.4	8.4	4.2/5 (3)	4.7/5 (1)	3.5/5 (1)	4.2/5 (5)	4	199	15	89.4
3	937	6.7	8.6	4.0/5 (3)	5.0/5 (1)	3.0/5 (1)	4.0/5 (5)	3	269	9	88.3
3	1,099	26.0	11.3	3.7/5 (3)	5.0/5 (1)	3.2/5 (1)	3.8/5 (5)	3	295	22	88.9
3	1,280	4.1	8.7	4.4/5 (3)	5.0/5 (1)	3.0/5 (1)	4.3/5 (5)	4	237	8	90.1
3	557	11.9	9.4	4.1/5 (3)	5.0/5 (1)	2.5/5 (1)	4.0/5 (5)	4	225	8	88.1
4	1,481	4.8	12.1	4.4/5 (3)	5.0/5 (1)	3.3/5 (1)	4.3/5 (5)	4	219	15	92.0
3	965	17.7	13.0	4.4/5 (2)	4.6/5 (2)	3.0/5 (1)	4.2/5 (5)	5	183	14	91.3
4	1,002	19.4	8.9	2.9/5 (3)	3.8/5 (1)	1.7/5 (1)	2.9/5 (5)	3	383	18	80.8

Scholar Dashboard

Nonetheless, it was noted that the peer and self-review scores were considerably higher than those of the instructor. However, if you evaluate the red and green sections, it is believed that there was concurrence with regards to the poorest and best performances. We believe that a pairwise selection by peer review and instructor would lead to a ranking that would be quite similar. We also believe that after students receive instructor scores, it will begin to calibrate the numerical scoring more closely to that of the instructor.



Correlation of Average Peer and Self Reviews (y axis) vs. Instructor Reviews (x axis)

Subset drawn from 55% of class with instructor scores complete (black line = identity line)

Student Feedback

A post-course survey was conducted. As one of the goals of the exercise was reinforcement of evidence-based medicine concepts and also to add higher order thinking around content they are learning, we asked the following questions and students rated their answers from 1 (Do Not Agree) to 5 (Agree Completely).

- The final Clinical Correlations exercise led to greater self-reflection on the nature of scientific knowledge and my understanding of it. Average Score: 3.17
- The final Clinical Correlations exercise, including the peer review process, helped me review and gain a deeper understanding of some course content. Average Score: 3.44
- The final Clinical Correlations exercise, including the peer review process, led me to review and gain a deeper understanding of the nature of peer review. Average: 2.97
- The final peer review exercise in Clinical Correlations helped reinforce the nature of scientific knowledge and the concepts of bias, biostatistics, and evidence-based medicine presented earlier in the quarter. Average Score: 3.09

Despite the neutral attitude scores, students answered 79% of the questions correct on endocrine physiology topics of the case-based summative examination, while averaging 70% on the remaining 60% of the exam.

Based upon these mostly neutral scores and specific student comments, we think that having the introductory experience with *Scholar* 2 weeks before final exams was stressful on the students. Some comments suggested that the *Scholar* experience should have been started sooner so they could be practicing its elements sooner within the quarter. Some students thought the goal felt more like a “physiology assignment,” which suggests that the scaffolding questions successfully directed them towards identifying perturbations of normal function. Some comments referred to just the opposite experience of thinking that the cases were expecting them to all interpret laboratory tests and make an accurate diagnosis. All real cases have data that is effectively a distractor to the most crucial aspects of the case.

Despite devoting a session to the team-building aspect of proactive peer review process, some students reported what they thought was “harsh and not constructive criticism.” Therefore, reducing the actuality or perception of time and grade pressure would seem to be crucial as we move the project forward. The case scaffolding questions always included a request to reflect on their learning issues. Despite directions to focus upon what they do know and to reflect on what they don’t, it is clear that often first year veterinary students themselves do not expect to be able to sort through real case information to find aspects for which they actually do have a knowledge background. In future applications we plan to extend the process of each phase of the *Scholar* case analyses over a longer period of time and to provide greater emphasis on the importance of each phase of the case exercises.

3. Fostering Critical Thinking Amongst First-year Medical Students

Background

A major challenge during medical school is making the transition from the basic science years to patient encounters in the unfamiliar clinical setting. It is our premise that a part of this ongoing problem is that many of our students are functioning at the lower order of thinking skills; memorization of facts together with some level of understanding. Further, during this transition, the medical student needs to develop the crucial competency of generating a differential diagnosis list. There is unfortunately little data available on how medical students acquire this skill (Bowen 2005).

Aims

The primary goal of this study is to assist first year medical students to critically evaluate clinical cases and become self-directed learners. In the process, we encourage the student to develop critical, analytical thinking by building upon accrued basic scientific knowledge. By encouraging students to assess each other's work, we aim not to only assist the student to develop critical thinking skills, but to also turn the students into their own teachers. Higher-level thinking skills are obligatory for developing the key competency of a differential diagnosis.

Methods

Students are presented with three clinical cases, based on material covered in the medical physiology class. The cases are designed in such a manner that it should foster critical thinking amongst students: Patient history → data acquisition → accurate problem representation → analytical reasoning → diagnosis. In this format, the student becomes an investigator.

Each student is randomly assigned to one specific case that they have to complete for presentation. However, all students have to study and report on all three cases. They are asked to prioritize their three top differential diagnoses based on their class instruction and by making use of the available resources. All resources have to be listed in their presentations. All this is done on *Scholar*. Each student is allowed a specific number of days for writing a first draft, at which time the other students have access to their work and are invited to do a peer review on the initial work. A student then has three days to collect the reviews, act on it if they chose and modify their initial draft into a final presentation. In this manner we involve the entire class with all three cases and allow for constructive support and criticism amongst the peers. The student then presents the case and his or her diagnosis to a small group of fellow students, who have acted as peer reviewers. Some outcome assessment is done by expecting the students to answer five questions.

Results and Future Directions

The students are only now completing the cases and the results are not yet ready for analysis. We hope that the results would inform us of the usefulness of a software resource such as *Scholar,* to assist students in making a correct diagnosis in a clinical case. We hope to determine whether students who were able to employ higher order concepts were able to construct a stronger differential diagnosis and were more likely to arrive at the correct diagnosis. Since a metacognitive approach can teach students to improve their learning (Grabera, Tompkinsa, and Hollanda 2009; Thiede, Anderson, and Therriault 2003), it is of interest to us to determine whether this approach to solving case studies would assist the student from shifting their medical education from knowledge recall to critical thinking. Our approach emphasizes the student's higher reasoning skills.

4. Computational Horizons: Data Collection and Learning Analytics for Complex Epistemic Performance

In further phases of this project we propose to extend the computational possibilities for machine assessment and machine-supported human assessment of complex epistemic performance, including:

1. *Multi-dimensional assessment predictor (supervised machine learning):* This assessment mechanism can learn from a set of training examples (i.e., assessed assignments) to automatically assess newly submitted assignments according to the multiple dimensions of grading rubrics.
2. *Clustering of assignments to support "batch assessment" (unsupervised machine learning):* This software tool can automatically cluster all the submitted assignments to identify "typical" categories of answers provided by the students. With a visual interface, such a tool can effectively support an instructor to perform "batch assessment", i.e., to classify an entire cluster of assignments if they are very similar. With multi-dimensional grading rubrics, we can support such batch assessments in each dimension. In comparison with the assessment predictor, this technique is less automatic, but it does not require training examples, and thus can be applied even before any assessment is done for an assignment.
3. *Intelligent prioritization of assessment to minimize human grading (active machine learning):* The assessment verification tool can be governed by active learning techniques to intelligently prioritize the tentatively already-assessed assignments for the instructor to verify so that the verified assessed example would be most useful for machine learning and thus would help most to improve the accuracy of the assessment predictor.
4. *Personalized assessment and feedback for individual students (behavior data mining):* This technique enables detailed analysis of student work in every rubric dimension to provide personalized assessment and feedback for each individual learner, including specific pointers to problematic areas. It can also be used to analyze all student assignments and their detailed grading results to reveal potentially interesting patterns of student learning behavior and performance. The discovered patterns can further be used to model an individual student's status of mastering, which enables personalized learning for the individual. Incidental learning activity data ('data exhaust': e.g. timestamps, keystrokes, edit histories, and clickstreams that show periods of engagement, forms of activity, navigation paths and social interaction patterns) will provide additional predictive analytics for both the instructor and the student.

Our team have already proposed a set of basic computational approaches for automated assessment and experimented with the proposed approaches in directions 1 and 3 above using a data set collected from a previous offering of the course taught by PI Ferguson. Our preliminary results have proven the feasibility of automating assessment by using the state of the art machine learning and text mining techniques, and demonstrated effectiveness of active machine learning for optimizing the collaboration of humans and machines in automated assessment with minimum human effort. A submission based on this work has been made to a major Computer Science conference on leaning at scale (Geigle, Ferguson, and Zhai 2016 Under Review). We plan to further verify these preliminary findings by doing more experiments using the data sets collected from this ILSDI-funded pilot project, and extend *Scholar* with the proposed technologies for automated assessment and learning analytics.

In sum, our general vision is to leverage *Scholar,* a powerful general learning infrastructure, and cutting-edge research in computer science, particularly machine learning, information retrieval, text mining, and machine learning, to enable teaching of critical thinking at large scale and effectively. The ILSDI funding has enabled us to deploy two courses in the veterinary medicine and medical school education on *Scholar* and collect data from both courses to further experiment with new computational methods that we have proposed or will propose for automated assessment and learning analytics. Our team are working on leveraging the collected data to generate preliminary results to support a grant proposal application to NSF that we are planning to submit in January 2016.

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APPENDIX

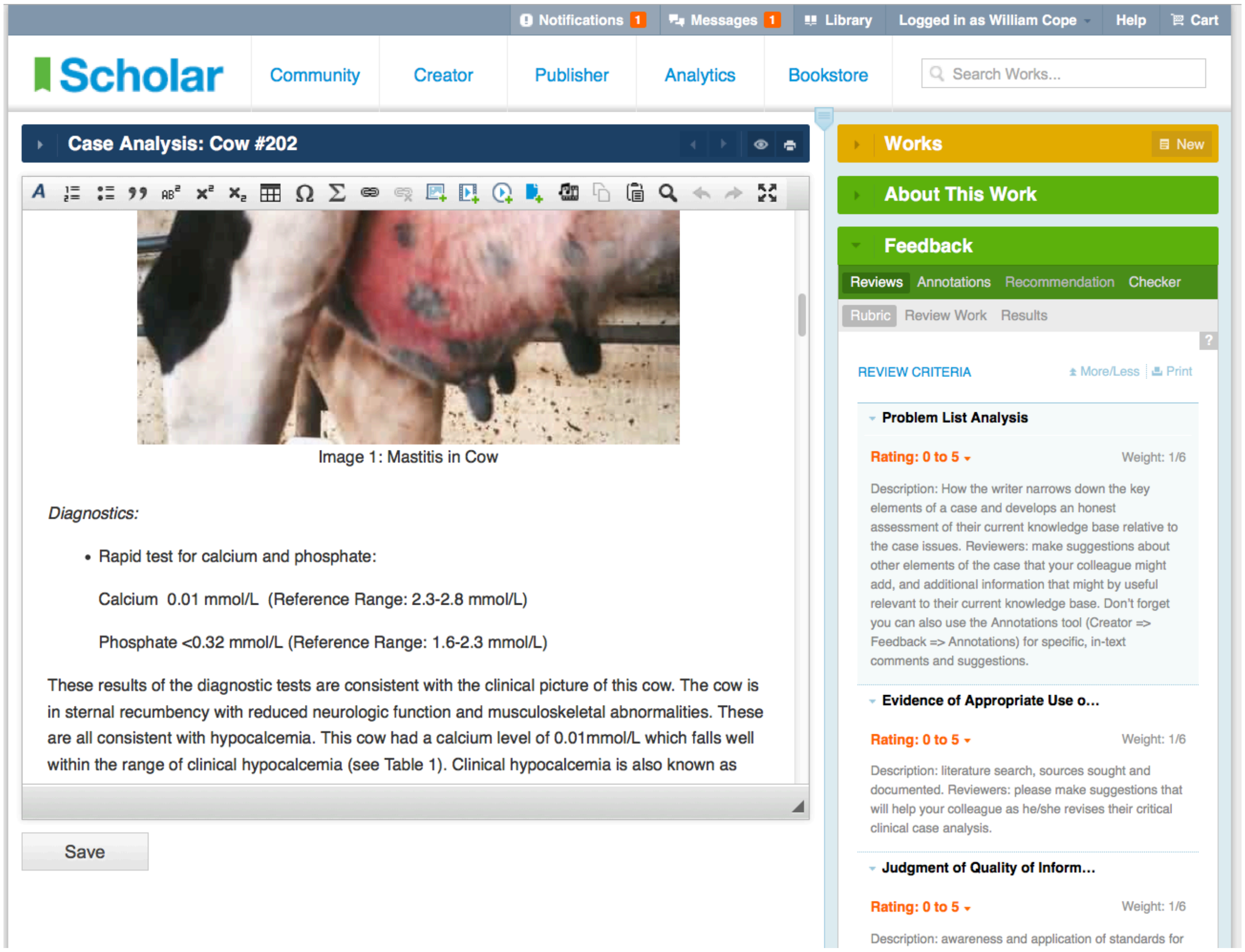


Fig. 1: Creating the first draft of the case analysis.

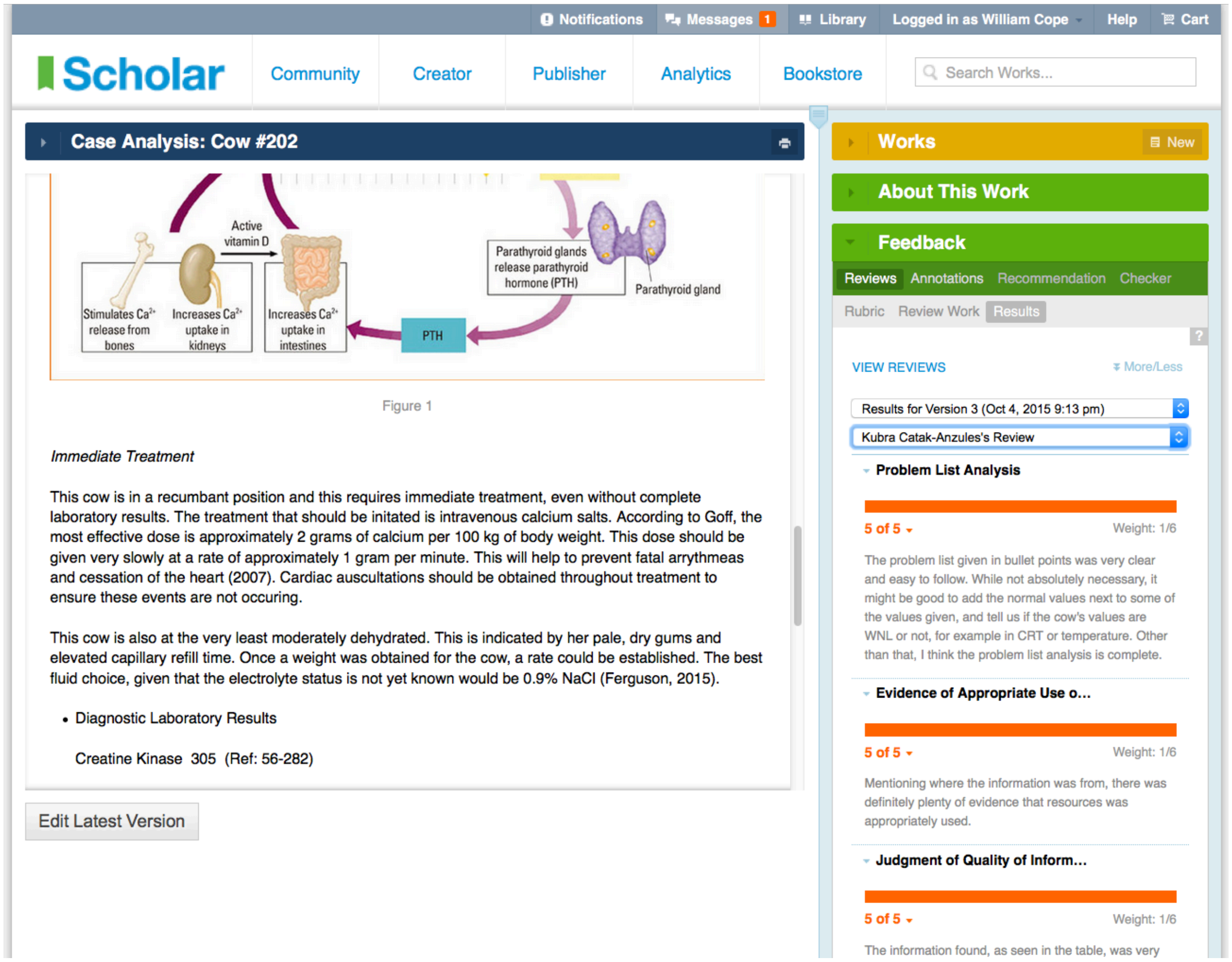


Fig. 2: Viewing peer feedback

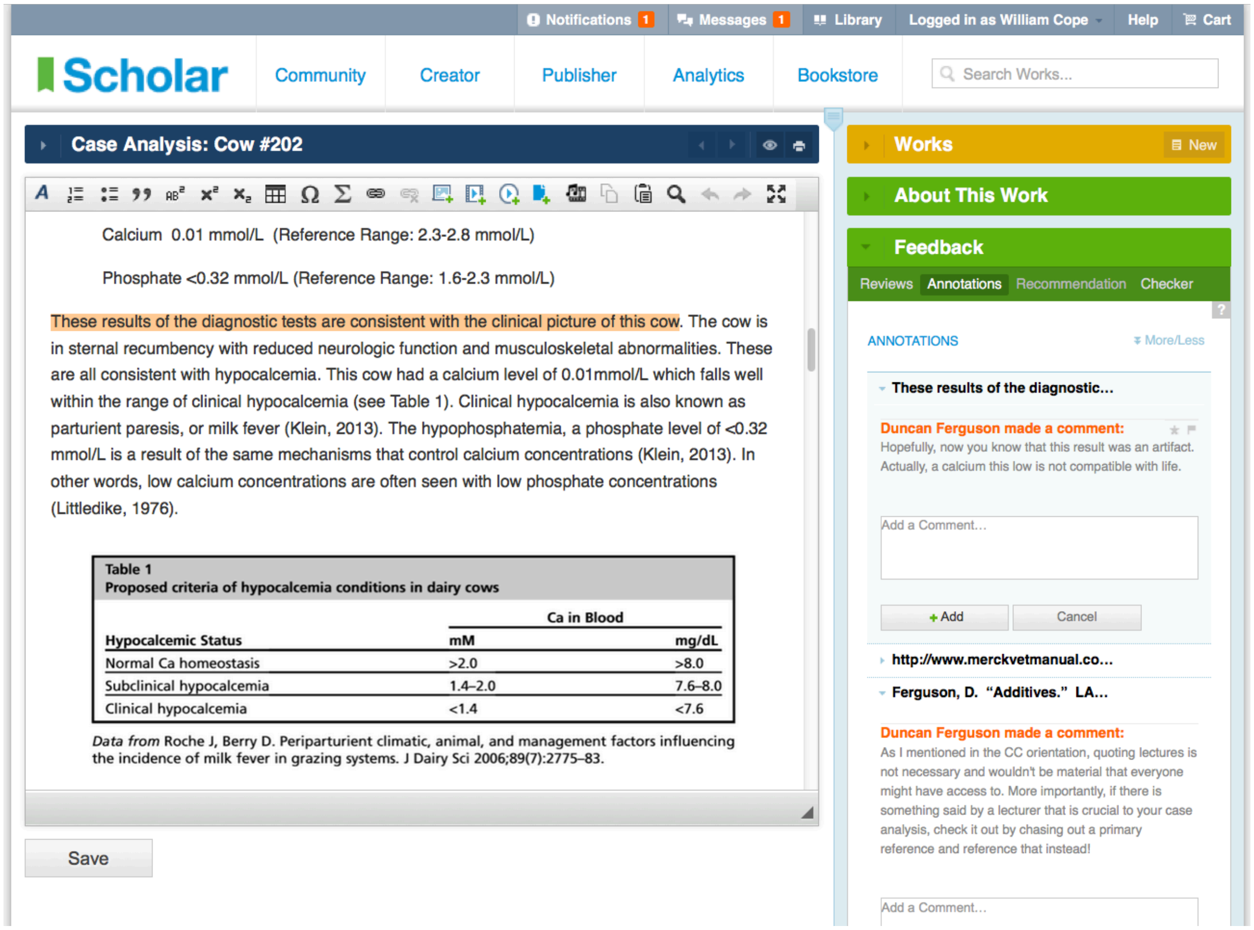
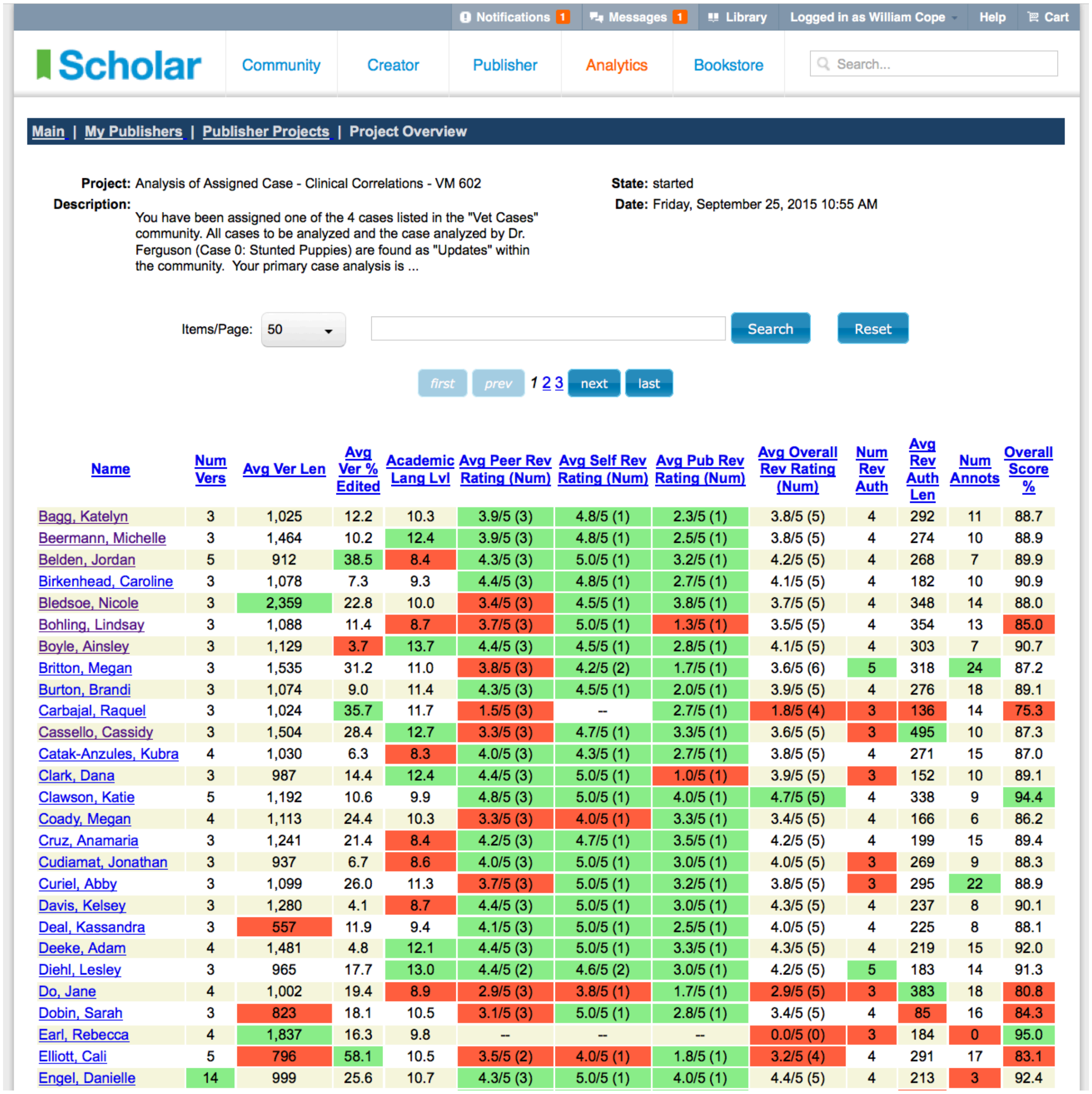


Fig. 3: Viewing Annotations



Name	Num Vers	Avg Ver Len	Avg Ver % Edited	Academic Lang Lvl	Avg Peer Rev Rating (Num)	Avg Self Rev Rating (Num)	Avg Pub Rev Rating (Num)	Avg Overall Rev Rating (Num)	Num Rev Auth	Avg Rev Auth Len	Num Annots	Overall Score %
Bagg, Katelyn	3	1,025	12.2	10.3	3.9/5 (3)	4.8/5 (1)	2.3/5 (1)	3.8/5 (5)	4	292	11	88.7
Beermann, Michelle	3	1,464	10.2	12.4	3.9/5 (3)	4.8/5 (1)	2.5/5 (1)	3.8/5 (5)	4	274	10	88.9
Belden, Jordan	5	912	38.5	8.4	4.3/5 (3)	5.0/5 (1)	3.2/5 (1)	4.2/5 (5)	4	268	7	89.9
Birkenhead, Caroline	3	1,078	7.3	9.3	4.4/5 (3)	4.8/5 (1)	2.7/5 (1)	4.1/5 (5)	4	182	10	90.9
Bledsoe, Nicole	3	2,359	22.8	10.0	3.4/5 (3)	4.5/5 (1)	3.8/5 (1)	3.7/5 (5)	4	348	14	88.0
Bohling, Lindsay	3	1,088	11.4	8.7	3.7/5 (3)	5.0/5 (1)	1.3/5 (1)	3.5/5 (5)	4	354	13	85.0
Boyle, Ainsley	3	1,129	3.7	13.7	4.4/5 (3)	4.5/5 (1)	2.8/5 (1)	4.1/5 (5)	4	303	7	90.7
Britton, Megan	3	1,535	31.2	11.0	3.8/5 (3)	4.2/5 (2)	1.7/5 (1)	3.6/5 (6)	5	318	24	87.2
Burton, Brandi	3	1,074	9.0	11.4	4.3/5 (3)	4.5/5 (1)	2.0/5 (1)	3.9/5 (5)	4	276	18	89.1
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Diehl, Lesley	3	965	17.7	13.0	4.4/5 (2)	4.6/5 (2)	3.0/5 (1)	4.2/5 (5)	5	183	14	91.3
Do, Jane	4	1,002	19.4	8.9	2.9/5 (3)	3.8/5 (1)	1.7/5 (1)	2.9/5 (5)	3	383	18	80.8
Dobin, Sarah	3	823	18.1	10.5	3.1/5 (3)	5.0/5 (1)	2.8/5 (1)	3.4/5 (5)	4	85	16	84.3
Earl, Rebecca	4	1,837	16.3	9.8	--	--	--	0.0/5 (0)	3	184	0	95.0
Elliott, Cali	5	796	58.1	10.5	3.5/5 (2)	4.0/5 (1)	1.8/5 (1)	3.2/5 (4)	4	291	17	83.1
Engel, Danielle	14	999	25.6	10.7	4.3/5 (3)	5.0/5 (1)	4.0/5 (1)	4.4/5 (5)	4	213	3	92.4

Fig. 4: Whole class analytics overview

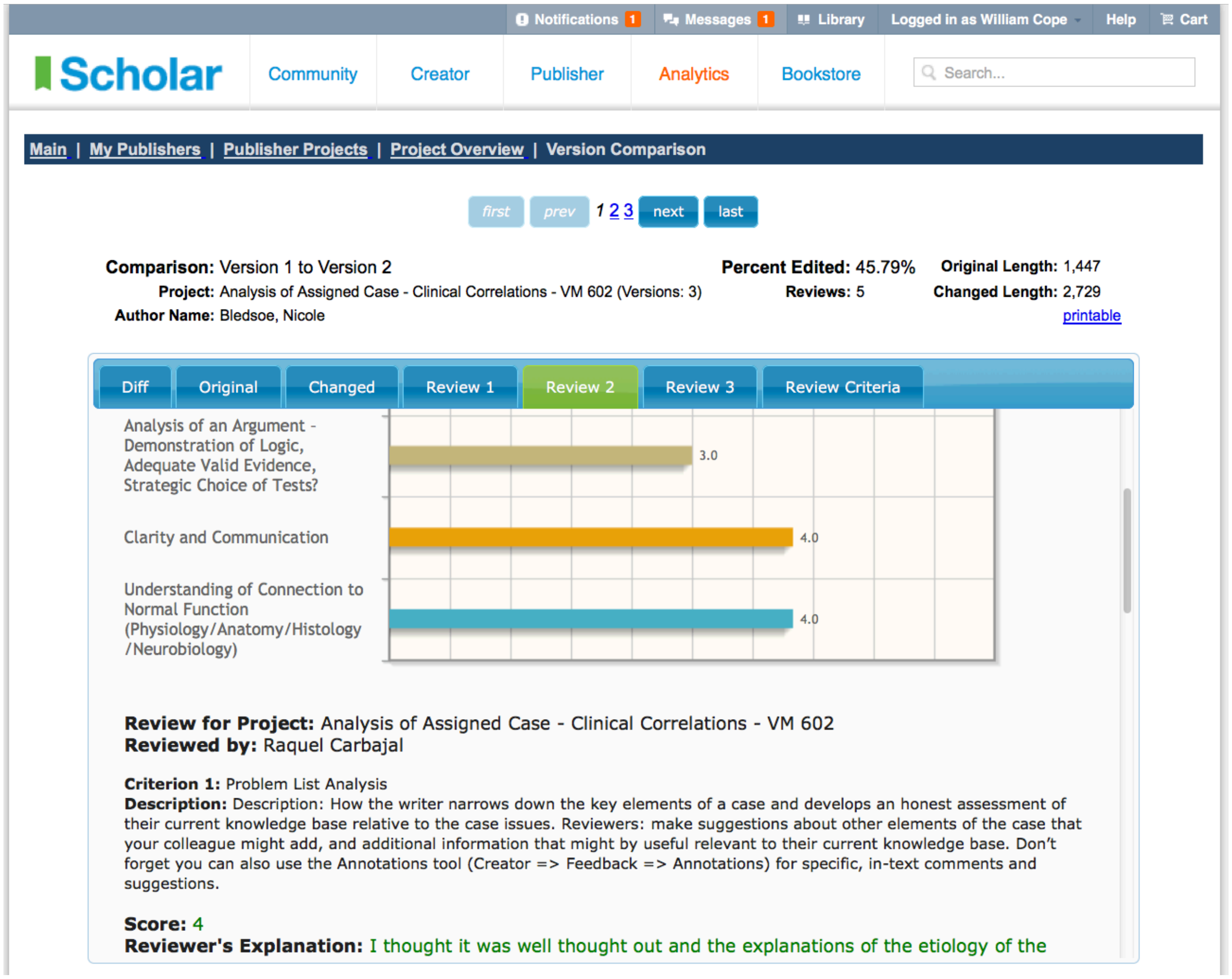

Fig. 5: Drilling down into the details of the development of an individual student's work, and the evolution of their thinking as the case develops