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Designing for student-facing learning analytics

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Despite a narrative that sees learning analytics (LA) as a field that aims to enhance student learning, few student-facing solutions have emerged. This can make it difficult for educators to imagine how data can be used in the classroom, and in turn diminishes the promise of LA as an enabler for encouraging important skills such as sense-making, metacognition, and reflection. We propose two learning design patterns that will help educators to incorporate LA into their teaching protocols: *do-analyse-change-reflect*, and *active learning squared*. We discuss these patterns with reference to a case study utilising the Connected Learning Analytics (CLA) toolkit, in three trials run over a period of 18 months. The results demonstrate that student-facing learning analytics is not just a future possibility, but an area that is ripe for further development.

Who is learning analytics for?

Learning analytics (LA) is a rapidly growing field aimed at understanding and optimising learning, and the environments in which it occurs (Siemens & Long, 2011). However, despite a declared interest in analytics for the learner, we continue to see solutions that are focussed on institutions and academics, in particular the identification of at risk students. This is no great surprise, as Ferguson (2012) noted early on; the social and political drivers behind LA meant that a clear case is often made for using data to help improve completion rates and educational results at institutional, national, and international levels. However, this historical dominance of student success models in the field (Dawson, Gašević, Siemens, & Joksimovic, 2014) means that many institutions appear to equate LA with the identification of student engagement patterns, a trend that has lead to claims that it does not help learning (e.g., Bain & Drengenberg, 2016; Ruggiero, 2016).

This is a poor argument to mount. LA has a far richer set of methods, frameworks, and tools available. These range from the automated content analysis of online discourse (Kovanović et al., 2016), to social learning analytics (Buckingham Shum & Ferguson, 2012), multimodal methods (Blikstein, 2013), and conceptual frameworks for linking learning design with instructor facing LA (Bakharia, Corrin et al., 2016). Anyone tempted to equate LA with the prediction of at risk students is encouraged to examine more recent Learning Analytics and Knowledge (LAK) conference proceedings for an indication of the extensive range and breadth developing in the field as it matures. Indeed, one difficulty that the field faces arises from this very breadth of approaches, many of which are mathematically and/or computationally sophisticated and can be difficult for non-STEM practitioners to use in their teaching practice. Furthermore, tools are often presented by different vendors as *black box* systems (Pasquale, 2015), and so do not allow teaching academics to engage with them in anything but a superficial manner. This encourages the ongoing perception of the field as something that is for administrators rather than learners and those who support them.

In this paper, we consider one subfield of LA that attempts to tackle this misperception head on: student-facing LA (Ferguson, 2012; Kruse & Pongsajapan, 2012; Sclater, 2017). We provide data from a series of three user trials, where student-facing LA was increasingly integrated into pedagogy and assessment. These trials were run over a period of 18 months, and were all coordinated by the same lecturer (Kate Davis). Each run made use of the Connected Learning Analytics (CLA) toolkit (Kitto, Cross, Waters, &

Lupton, 2015). This is an LA tool that collects data from a range of "in the wild" learning activities that eschew the Learning Management System, instead making use of standard social media tools and resources (e.g., Twitter and Facebook), and presents both instructors and students with dashboards (i.e., visual representations of their data) to help them understand and make sense of the data traces left behind. We demonstrate that student-facing LA solutions such as this can be used to encourage students towards more sophisticated metacognition about their own learning processes. This is a field ripe for further development.

Student-facing LA

LA has placed surprisingly little emphasis upon providing the learner with tools that they can access to understand their own learning processes. This leads to a lack of learner agency and control over the data they generate while learning, which in turn may lead to privacy and ethical concerns (Drachsler & Greller, 2016; Slade & Prinsloo, 2013). Even avoiding this contentious area, failing to provide learners with access to their learning data diminishes opportunities to encourage student sense making, metacognition, and reflection. The widely recognised importance of encouraging these processes in education makes the failure of LA to provide an extensive range of student facing tools even more surprising. It is hard to imagine why LA data could not be used in a student-facing context, however issues of predictive agency and control often arise. For example, a student who is told they are at risk, could believe the LA system that makes the prediction, and act on it by dropping out, rather than deciding to work harder to prove it wrong. LA is not merely reporting upon reality. In some cases it has the very real potential to create it, and it is essential that we develop a form of *algorithmic accountability* in our use of learning data (Buckingham Shum, 2016). These issues are discussed more fully in the companion paper to this work (Kitto, Lupton, Davis, & Waters, 2016). In this paper we focus upon discussing evidence that LA can indeed be used in a student-facing context.

Student-facing solutions are often presented as a dashboard, where some sort of information trace is aggregated, and perhaps analysed, and presented to the student in a digestible form. For example, Arnold (2010) provided an early dashboard, in the form of a traffic light system, where red was used to indicate behaviour that was strongly suggestive of failure, yellow a warning, and green an all clear. In this paper, we will restrict our definition of student-facing LA to solutions that enable students to view their own data via a dashboard, in order to interpret and act upon it in some way, but we acknowledge that other forms are possible. For example, Pardo, Jovanović, Dawson, Gašević, and Mirriahi (2017) make use of an automated emailing system that sends each student a personalised message about their patterns of behaviour. This encourages reflection, catching up, or extension depending upon past actions.

Previous research on student-facing LA dashboards has explored a range of tools and applications. For instance, one study demonstrated that students can understand simple dashboards describing their learning processes and participation (Corrin & de Barba, 2014), while a second study showed students interacting with dashboards which summarised weekly engagement with course materials (Kahn & Pardo, 2016). Of particular interest, the second study found that students move through a quick learning phase while they are discovering the utility of the dashboard. After this stage they tend to relax, only checking back on a weekly basis to ensure that their behaviour patterns are keeping on track when compared to the rest of the cohort. Similarly, Sclater (2017) discusses a number of case studies as examples of the student-facing delivery of information about engagement in class activities, such as the Jisc student app (see https://analytics.jiscinvolve.org/wp/category/student-app/). These approaches tend to place emphasis upon the analysis of reports about where the student is when compared to the rest of a cohort. They do not encourage reflection or metacognition about anything other than basic activity patterns.

This highlights an important point. To date, the bulk of the work that has been completed on student-facing LA has been somewhat naïve. It is rarely coupled with pedagogical approaches, and often consists of a one step process. That is, students do something in a class, and some analytics are used to inform them about their participation in this activity. They are not required to do anything with this newfound knowledge. Lockyer, Heathcote, and Dawson (2013) have introduced the notion of checkpoint analytics, to describe this scenario. In this case, LA gives advice on whether a student has met the prerequisites for learning by assessing whether they have accessed the relevant resources. In contrast, process analytics provides insight into learner information and knowledge processing within a set of tasks. In the example used by Lockyer et al. (2013), there are a number of points throughout a complex whole-of-course process where social network analysis can be used to inform staff and students about patterns of behaviour and engagement. Similar arguments have been made by Kruse and Pongsajapan (2012), and Wise (2014), who discuss ways in which students might be encouraged towards metacognition and reflection, but few concrete working examples of how this might be achieved have been presented to date. The reflective writing analytics (RWA) that have recently been developed at University of Technology Sydney (Buckingham Shum et al., 2016 Gibson et al., 2017), provides an example of an early prototype tool where LA is used to encourage students to reflect upon analytic reports that aim to improve their writing. However, we are yet to see such processes move into the mainstream, or the development of sophisticated pedagogical approaches that might utilise them.

Why is this so? One reason lies in the difficulties of translating current analytics dashboards into the classroom. Here, we see the dominance of student retention and success models, where the analytics presented by commercial solutions tend to treat learning as equivalent to the completion of a series of superficial activities (e.g., watching videos), often in an aggregated format (i.e., with no information as to who watched the video, or when, and what they did next), which individual academics cannot drill into. Furthermore, they fail to provide analytics that enable contextualisation to ongoing classroom activities. On the other side of the divide, it can be difficult for educators to imagine how students might use educational data, much less design student oriented LA solutions that promote reflection, metacognition, and sense-making.

Strategies for achieving more learner centred LA have been proposed. For example, Verbert, Duval, Klerkx, Govaerts, and Santos (2013) suggested a learning analytics process model that considers four stages: *awareness, reflection, sense-making,* and *impact*, but in the survey they conducted of existing dashboards, a minority had a student-facing focus, and none addressed the problem of impact. It is challenging to find ways in which students can be encouraged to look at and use their data in the context of a specific course. While it is relatively easy to motivate the use of student-facing dashboards in a class that uses reflective practice, few sophisticated models have been developed. There is a tendency for studies to show students a dashboard and to perhaps conduct interviews or surveys to explore usage (e.g., Arnold & Pistelli, 2012; Corrin & de Barba, 2014; Khan & Pardo, 2016; Muldner et al., 2015). We are not aware of any pedagogical models where students were required to act in response to the information seen in an analytics dashboard, by using some sort of well-scaffolded activity. Even the more sophisticated approaches (e.g., the RWA approach discussed above) tend to adopt a "go and look at it" pedagogical approach to utilising the provided LA dashboard.

One strategy could be to use student-facing LA in an assessment structure, but few attempts to do this have been made. This is perhaps because of the research status of LA, and associated ethical requirements that students be able to opt out of studies, which can make it difficult to use standard assessment models. How then are we to proceed? At this stage, LA requires input from pedagogical experts, who can construct complex learning activities that make use of the different sophisticated analytics that are available, and use them to encourage further metacognitive activities. However, an interdisciplinary gap between computer scientists and educators has made this potential contribution difficult to achieve. Many of the people who would be most interested in exploring novel ways in which LA might be incorporated into class-based learning designs do not have the programming skills necessary to develop their own technologies. This leaves them hostage to vendor provided solutions, which as we discussed above, often fail to provide information that they or their students find useful or relevant. Even more problematic, a lack of awareness about the wide variety of ways in which data can be analysed and represented means that educators often underestimate the abilities of data science and what it might be able to achieve. The collection, analysis, and use of student data occurs at multiple intersections, and a range of stakeholders, ideologies, assumptions, and beliefs are involved. It is essential that all concerned parties are welcomed at the table, and given tools that will facilitate their participation in the field.

Using learning design patterns to develop student-facing LA

Helping educators to make use of student-facing LA will require not just technological solutions, but a series of effective learning designs (LD) that are general enough to encourage wide-ranging use, but which can also be adapted to class specific contexts. Technology enhanced learning (TEL) design patterns (Dalziel, 2014; Goodyear & Retalis, 2010) offer a potential way to proceed. Developing such LD patterns that make use of LA at their core would make it possible for educators to take solutions "off the shelf" and adapt them to their own requirements, while enabling the ongoing development of general technological solutions that would help educators to realise these rich data based LDs.

Design patterns have been critiqued as reductionist and there is ongoing discussion about granularity, abstraction, and pattern quality, and the resultant utility of generic TEL design patterns (Kohls & Wedekind, 2011; May et al., 2016; Mouasher & Lodge, 2016; Yishay & Winters, 2007). However, in this case we feel that they are likely to offer a conversation starter between two fields that have so far not managed to engage in a particularly productive dialogue. LD patterns can provide a way in which educators might think about the more sophisticated opportunities that arise when learners are given access to rich data and analytics about their learning journey. Furthermore, LD patterns can help data scientists understand what analytics are likely to assist learning, rather than just reporting base level activity data.

In the following section, we sketch out two LD patterns that use student-facing LA, both of which were first presented in Kitto et al. (2016). We extend the research presented there with an analysis of data obtained from a series of three trials where these two patterns have been tested using the Connected Learning Analytics (CLA) toolkit (Kitto et al., 2015), over a period of 18 months. We will show that some students are capable of both exploring and interpreting LA reports about their behaviour in online communities, but that careful attention must be paid to assessment structure and scaffolding, creating meaningful opportunities for reflection, and existing student capabilities.

Do-analyse-change-reflect

The first LD pattern is a basic building block consisting of four phases:

1. Do: Students are instructed to participate in some sort of activity. Perhaps they prepare for a flipped class by watching videos; maybe they write a blog post and then comment on three of their classmate's blogs. The possibilities for this step are potentially infinite, as long as it is possible to collect data arising from this initial learning activity. LMS data, social media APIs, (or Application Programming Interfaces, the acronym is now more common than the full term) mobile apps, and online games all provide examples of tools that might be used to collect such data. This could take the form of timestamps, actual written text, audio visual recordings, structural characteristics of interactions (i.e., student 1 replied to student 2), interaction data, and clickstreams, but many other data sources could be identified as the field of LA matures.
2. Analyse: Students are encouraged to consider LA dashboards that result from the *do* phase. Reports and tools from standard LA toolboxes could be used, or new ones developed, depending on the teaching context and learning objectives of a specific activity.
3. Change: A well designed LD pattern that makes use of student-facing analytics would then encourage a student to consider changing their behaviour as a result of the analytics that they see in the *analyse* phase. They could then iterate through a continuing sequence of *do-analyse-change* cycles, or perhaps the LD only requires a single iteration.
4. Reflect: Finally, students should participate in a reflective process where they explain what the LA reports revealed about their behaviour, how they made sense of their behaviour, and whether they decided to change as a result (and how).

We consider a final *reflect* stage to be essential to the effective implementation of this LD pattern. A common scenario in student-facing LA implementation typically involves students being shown a dashboard, being interested in it, but then failing to consider what it means to them (Verbert et al., 2013). It is important that the change phase be driven by a reflect phase to encourage students towards higher order critical thinking. One strategy would be to assess the change phase formatively and the reflect phase summatively, as this would encourage students to explore and try out new things, without fear that this would affect their final grade. However, we can imagine that other options might arise in specific circumstances.

The utility of this LD pattern stems from the core question that students are asked to consider: Are my self-perceptions reflected in my profile data? Khan and Pardo (2016) encouraged students to consider an activity dashboard that showed them how much time they spent in class activities compared to the rest of their cohort. However, the lack of the final reflect phase in that study may have led to students examining the dashboard but not being motivated to change their behaviour. In that case, a full implementation of the above pattern would have required an extension where students made use of the analytics to justify an ongoing change in their behaviour, perhaps over one simple activity, or perhaps over a longer period. We note that some students may opt to change their behaviour for reasons other than those they observe in their analytics profile, for example they may have a discussion about the usefulness of their contribution to an online forum with a classmate. This is not a problem for the pattern. Indeed, a careful reader will note that the pattern could be applied to a class context without making use of LA at all, this is a point that we shall return to in the discussion.

The critical self-analysis that is encouraged by the basic do-analyse-change-reflect pattern could be helped through the use of other LD patterns that build on it. For example, it is possible to automate the detection of cognitive presence in a community of inquiry (CoI) framework (Garrison, Anderson, & Archer, 2000) using recent advances in machine learning, with the current best performing classifier reported by Kovanović et al. (2016). However, the accuracy of this classifier is not perfect: currently sitting at an accuracy of 70.3% for one specific dataset. The complexity of the cognitive presence construct, and the contextuality of educational discourse makes it unlikely that classifiers such as these will ever achieve perfect accuracy. However, recent pilot trials have shown that students can struggle to achieve even this level of accuracy when classifying posts. For example, Table 1 shows results from a trial (discussed later in this paper), where participants were given a brief on screen tutorial explaining cognitive presence, and were asked to classify their posts according to this construct. We can see that no students achieved an accuracy equivalent to the classifier, which was trained on a large dataset collected elsewhere. The classifier achieved an accuracy of 47.3% when run on the same data (Kitto, Waters, Kovanović, Gašević, & Dawson, 2017).

Table 1
Classification accuracy (percentage of agreement) compared to an expert defined ground truth obtained by students (participant) in Trial 1 when classifying their posts (number of posts classified is indicated by the classified category).

Participant	A1	B1	C1	D1	E1	F1
Classified	8	10	7	19	4	18
Percentage of agreement	12.5	33.3	20.0	18.1	0	5.0

Despite this low level of student-based classification accuracy, such a learning activity can help students to reflect upon their behaviour, and perhaps change. But the low level of accuracy suggests they require scaffolding to understand how their behaviour might be classified using complex educational constructs. This raises an intriguing question. Can we use classifiers in a different way, for instance to make use of the current generation of imperfect classifiers as a scaffold for students as they develop reflective practice and metacognition? The *active learning squared* pattern aims to do this by building a more sophisticated pedagogical pattern on top of the basic do-analyse-change-reflect pattern.

Active learning squared

The active learning squared pattern arose from the problem where classifiers are never perfectly accurate, especially in the complexity of an educational setting. This makes it difficult to justify using them in education, where poor classifications can lead to adverse student outcomes. The active learning squared pattern serves two purposes: (1) it scaffolds the student, providing them with a quick way in which they might start using content analysis techniques to understand their behaviour; and (2) it avoids the need for a perfectly accurate classifier, by placing the student in this classification loop, giving them an opportunity to consider the way in which their behaviour has been classified and then to correct the classifications if they think they are incorrect. This means that both the student and the algorithm are learning in the process: the student is encouraged to learn about their own learning processes, and the algorithm is acquiring a data set that is specific to the particular class context over which it is running.

The active learning squared pattern consists of the following sequence of steps (which could be used with any educationally relevant classifier – not just cognitive presence):

1. Do-analyse-change-reflect: Students participate in a learning activity and their data is harvested in some way (as was discussed in the previous pattern).

2. Classify: Machine learning is used to classify the behaviour patterns of students. This provides a preliminary scaffolding step that helps the student to think about their own behaviour in the next phase.
3. Examine: Students examine a dashboard that shows how their aggregated behaviour in the do phase has been classified. They are informed that the classifications could be incorrect. They are also encouraged to compare their own perceptions with the data displayed in the dashboard.
4. Relabel: Students are encouraged to challenge and relabel a classification if they think that it is incorrect.

This approach has an added benefit in the way that it opens up the black box of machine learning to students. It helps them to understand how machine learning is used to classify their behaviour, and that it can often be wrong. Thus, this LD pattern serves to enhance the data literacy of students, which will become an increasingly important skill in coming years.

For the trials discussed in this paper, the active learning squared pattern extends the do-change-analyse-reflect pattern with a cognitive presence report that students are encouraged to engage with and challenge (Kitto et al., 2016). In this case, students are given a very brief one page tutorial about what cognitive presence construct is, and then encouraged to enter into an activity where a classifier scaffolds them during their analyse phase. A screen shows them how specific posts they have made in their learning community have been classified, and instructs them to think about this classification and to correct it if they think it is wrong. They are also encouraged to record reasons for this reclassification, and to highlight features in the post they think are indicative of their new classification. Figure 1 is a screenshot of this main activity screen.

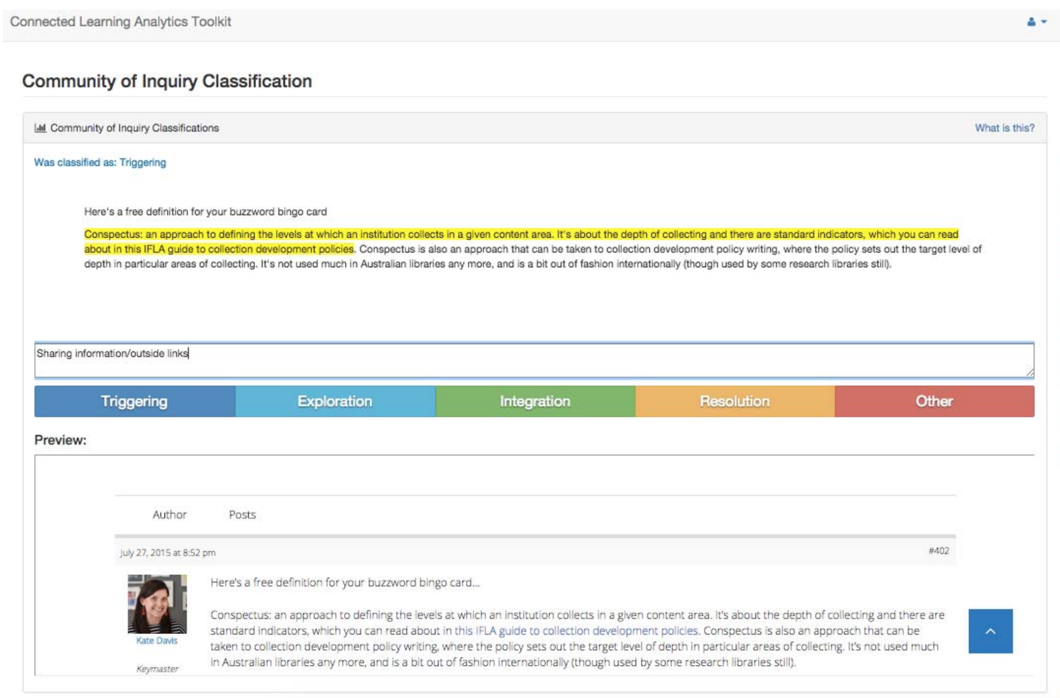

Figure 1. The main activity dashboard used for the active learning squared pattern

In the following sections, we report on a case study of three trials where we designed and implemented these patterns with increasing sophistication using the Connected Learning Analytics (CLA) toolkit (Kitto et al., 2015).

Case study: Using the Connected Learning Analytics (CLA) toolkit

The Connected Learning Analytics (CLA) toolkit (Kitto et al., 2015), has been designed to enable those educators who are teaching in the wild using standard social media, to utilise the benefits of LA. It makes use of the Experience API (xAPI) to unify the description of data gathered from various media, and a Connected Learning Recipe (or xAPI Profile) to unify the syntax and semantics of data gathered from these disparate media (Bakharia, Kitto, Pardo, Gašević, & Dawson, 2016). At present, data harvesting has been implemented for Twitter, Facebook, WordPress and YouTube comments, Trello, and Github. Contextualised activity, social network, and content analysis reports are available for instructors, along with student-facing dashboards (Figure 2), giving individual students access to amalgamated reports about their participation in learning activities that make use of the CLA toolkit.

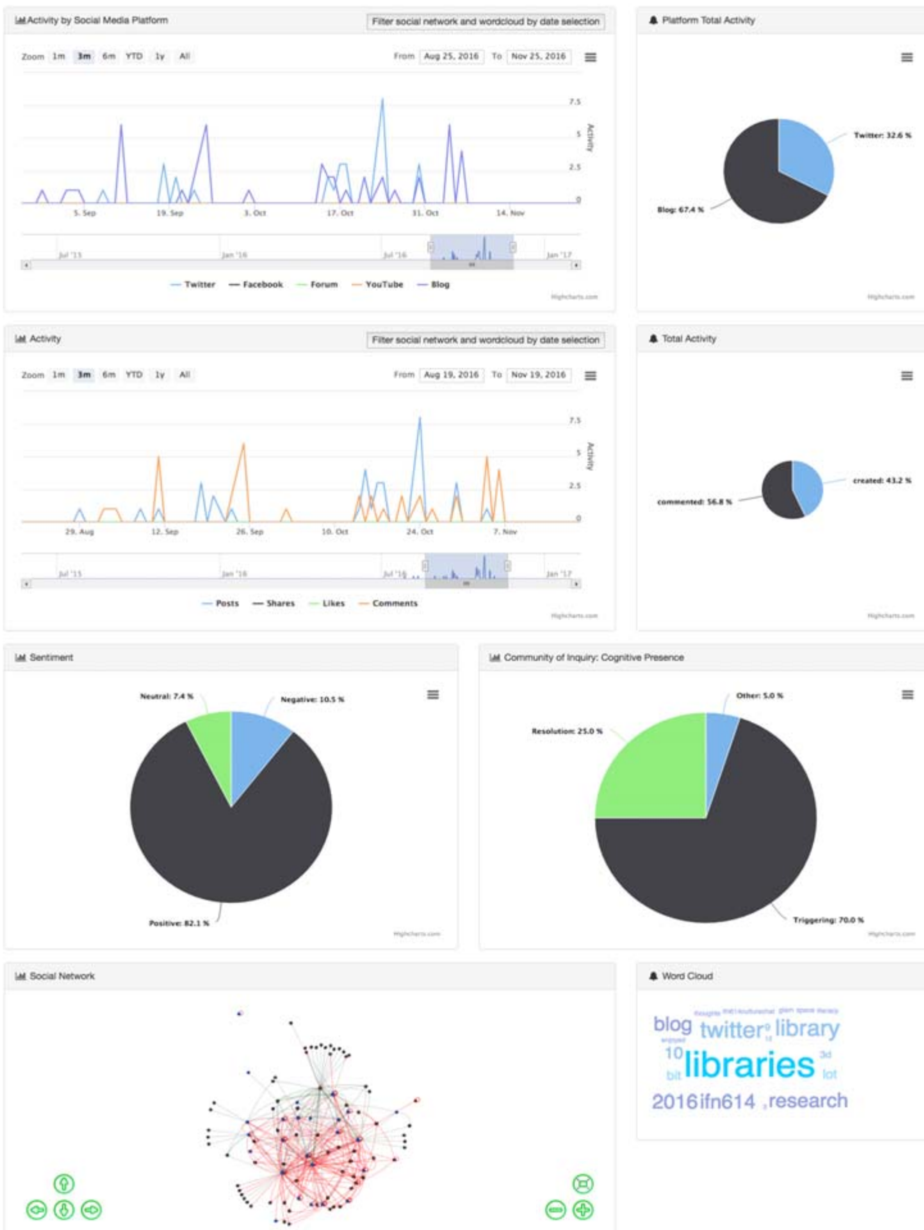

Figure 2. The student dashboard used in the trial for IFN614, displayed for one student (identifying information removed)

As a tool that is still in development, the CLA toolkit has only been trialled in a few specific class contexts, and always in an opt in mode (as per the conditions under which ethical approval for this research project was obtained). In this section, we present three trials of the toolkit in two classes (Table 2). In each case, the same instructor coordinated the units using her own WordPress installations, rather than the Blackboard LMS environment that is the standard offer at the university. A core objective for each of the classes used in these trials is to encourage students to actively engage in a learning community. This entails engaging with course content not just through teacher-provided material, but also through each other's content, and participating in meaningful discussion with each other around that content. Engagement in the learning community supports the aims of both courses by encouraging students to think about what it means to contribute to a community, and motivating them to get involved by tying the activity to assessment.

Table 2
Sequence of trials of the CLA toolkit

Unit	Semester	Aim/pattern	Linked to assessment	*N*
IFN614 Information Programs	S2, 2015	Piquing students curiosity	No	12
		active learning squared		6
IAB260 Social Technologies	S1, 2016	Do-analyse-change-reflect	Yes	17
IFN614 Information Programs	S2, 2016	Do-analyse-change-reflect (predict, compare)	Yes	11

Trial 1: IFN614: Information Programs, Semester 2, 2015

Aim
IFN614 aims to embed students in online professional networks, starting with the development of a network of their peers, but also extending beyond the cohort to connect with industry professionals.

Design
IFN614: Information Programs is a core unit in the Master of Information Science program (although it is available as an elective to students across the university). It is offered in a flexible delivery mode, with both on campus and online cohorts, and students are invited to move fluidly across enrolment modes from week to week. The unit was hosted on a WordPress installation that used a membership plugin called Ultimate Member to provide social functionality, along with bbPress to implement discussion forums. Each student had their own personal blog on the site where they posted their weekly activities, and could use the forums to ask questions about assessment and unit content. The class website and student blogs are available at http://2015.informationprograms.info.

Assessment
A blogging assignment worth 50% of their final grade required students to post weekly critical reflection activities on their personal blogs. Posts covered a range of topics related to unit content, and comprised 40% of the final grade. The blogging assignment also required students to actively contribute to the learning community by commenting on their peers' posts, engaging in discussion using the social functionality on the site including the forums, or using social media, for example Twitter, with the unit hashtag. Engagement in the learning community comprised 10% of the final grade.

As the CLA toolkit was still in the early stages of development it was not integrated into the assessment design in this iteration of the unit. Students were invited to sign up in week 8 via a post on the unit site. Recruitment focused on piquing students' curiosity and played on their interest in data and classification. Although students were not clear on what they should do with the CLA toolkit, they were still interested in signing up and having a look at their data in the dashboard. Students who had signed up were notified about the new active learning squared functionality, and given 1 week to engage with this feature in a small pilot study. Of the 34 students enrolled in the class, 12 signed up for the trial, with 6 students trialling the active learning functionality at the end of the semester.

Findings

This first trial adopted the go and try it approach we criticised earlier in this paper. While greater than one third of students signed up for the trial (12 out of 33), few made use of the analytics that the CLA toolkit provided in any of their weekly blogging assignments. As the LA offered by the CLA toolkit lacked an assessment driven purpose it is not clear whether usage impacted on students' learning (although we would expect that any impact was minimal). Six out of the total of 12 participants trialled the active learning squared functionality when it became available, but none explicitly reflected upon what they learned during that activity in their assessed reflections. More detailed findings in relation to trialling the cognitive presence classifier are reported elsewhere (Kitto et al., 2016; Kitto et al., 2017).

These findings were discouraging. However, on further consideration we realised the lack of a clear coupling to the assessment structure of this course was a possible explanation for the apparent failure of the trial to demonstrate any benefits from the student-facing analytics. This realisation led to the development of the LD patterns that are reported here. These were first reported by Kitto et al. (2016). The next two trials demonstrate their increasing integration into the instructor's teaching practice.

Trial 2: IAB260: Social Technologies, Semester 1, 2016

Aim

IAB260 aims to teach students about how people use social media as part of their everyday lives, exploring the way in which people construct personal and professional online identities.

Design

IAB260: Social Technologies is an undergraduate unit for students in the Bachelor of Information Technology. It is a core unit in the Social Technologies minor. In Semester 1 2016, the unit ran on a WordPress Multisite installation that used BuddyPress to facilitate social networking. Each student had their own blog on the unit site, which is available at http://2016.socialtechnologi.es.

Assessment

A blogging assignment required students to post weekly critical reflection activities on their personal blogs and was worth 50% of their final grade. Posts covered a range of topics related to unit content. Students were also required to complete a number of activities that asked them to *play* with social technologies and post about it on their blog, or to share articles, videos, or tools with their peers via their blogs. Blog posts comprised 40% of the final grade. Active contribution to the learning community was worth 10% of the final grade. This included commenting on peer's blog posts, engaging in discussion using the social functionality on the site, or using Twitter with the unit hashtag.

The do-analyse-change-reflect pattern was designed and implemented as follows:

1. Do: The blogging assignment was introduced in the first week of semester. Students set up their blogs on the unit site and began completing critical reflection blog posts.
2. Analyse: The toolkit was introduced in week 5 via a blog post on the unit site, however, take up was initially very low. In week 9, the unit content focused on quantified and connected lives in the context of exploring the quantified self movement. Students participated in a workshop that presented the LA offered in the CLA toolkit as an example of the quantified and connected self. Just prior to this workshop, students were provided with the reflective prompts for their final blog post, which asked them to consider their contribution to the online community during the semester. Attendance at the workshop was low (8 of 68 students). A series of further blog posts and videos encouraged them to sign up, resulting in a final uptake of 24 students right at the end of the unit (when the reflective prompt was due).
3. Change: Students were encouraged to think about how they were contributing to the community based on looking at their data in the CLA toolkit dashboard, however low uptake right until the end of the semester meant that this step was not realised in the way that we had anticipated.
4. Reflect: The reflect stage was built into the unit assessment, with students being asked to reflect on their contribution to the learning community during the semester. Students were encouraged to use the CLA toolkit to assist them with writing this reflection.

The following prompt questions were used to guide students' final reflections on their participation in the learning community for this trial:

In this part of the reflection, we want you to reflect on your contribution to the learning community this semester. Tell us:

- how many comments you made on your peers' posts,
- why you commented as much as you did, and what factors influenced the volume of your contributions,
- about any trends you noticed in your activity around the site,
- what topics you talked about, and
- about the quality of your contributions – the value you added to the conversations.

You should use data to justify your claims here. How can you support your claims about your contributions to the learning community with evidence?

Findings

Of the 68 students enrolled in IAB260, 24 students signed up for the trial with 17 students explicitly drawing on the CLA toolkit in their reflections. This heightened use of the CLA toolkit in an assessment item is attributed to the direct mention of it in instructions about how the assessment task could be completed. Students' reflections were analysed according to their quality. We created a taxonomy based on the students' responses and used this to classify the posts (Table 3).

Table 3

Quality of students' posts in IAB260, 2016

Score	Level of analysis	*N*
1	Included some/all graphs with no reference or analysis	3
2	Included some/all graphs, basic quantitative analysis relating activity to personality and/or interest	12
3	Included some/all graphs, compared & contrasted, mentioned qualitative aspects	2

The quality of reflections using the CLA toolkit as evidence varied from including screen clips of the graphs in the dashboard with no reference to the data, to basic interpretation of the graphs explaining the pattern of activity and use of tools, to highly reflective commentary on the data, such as comparing and contrasting the graphs, and commenting on the quality of their work. However, the majority of students (N = 12) confined their analysis to commenting quantitatively on their activity. They explained their activity in relation to factors such as their interest/lack of interest, personality and life balance:

> To be honest I didn't comment on many post despite the fact I have to. I didn't feel comfortable commenting due to online experience from Reddit (state your opinion and other will bash you for it) thus **I really hate making comments and tend to stay behind the scene or lurking** but that does not mean I did not comment at all. You can see the analysis from the toolkit below [timeline graph]. Between 23 May and 6 June, there was a spike for comments. Apparently because I was in the mood of making some comments so that happened. You may see I didn't make many comments as **I only commented on topic that intrigues me or the one that I'm familiar with**. The other thing I notice is my sentiment which you can see below [pie graph] 77% percent positive. I always end up being positive online as usually, people won't find much to argue when I react positively compared when I react negatively. [our emphasis, score = 2]

More sophisticated responses used evidence from the CLA toolkit to explain and interpret the quality of engagement. For example, this student explained that she made an effort to expand on her peers' ideas (although she was surprised that she didn't see this reflected in the toolkit):

> This chart shows the nature of my contribution – it is mostly in the 'triggering' category. In terms of critical thinking and cognitive presence, this means that my content acts as a trigger for ideas and thoughts. **I thought that I would have more percentage in exploration** as well, since a lot of comments I've made asks thoughtful questions which are relevant to the blog post (examples shown later on). The following screenshot is also taken from CLA toolkit and it shows the different types of contents I've commented on my own posts as well as my peers'. **I've tried to expand on the original ideas from their blog**

> **posts and add my own viewpoint in by linking materials in which they might find helpful/relevant to their topic**. I know my comments tend to be a bit lengthy but I feel like there is a lot to discuss after reading a blog post so I want to talk about them in the comments. I hope to encourage a thoughtful discussion with my peers through that and maybe develop new ideas together with them. [our emphasis, score = 3]

We note this should not have been particularly surprising, as the classifier for cognitive presence this student refers to is not particularly accurate. This was the reason for releasing the active learning squared pattern generally, but few students appeared to understand this point throughout this trial. We shall return to this important point in the discussion.

Another student was surprised at the data, cross referenced data, and commented on wanting to expand his horizons:

> This [pie graph displaying commenting vs creating] actually **comes as a bit of a surprise**, as I originally thought it [commenting activity] was lower. I think the reason for this is the fact that my commenting behaviour has been pretty sporadic (see the activity chart below for an example). If there was anything I'd change going back, it would be putting more effort into commenting. Frequency would be one thing to consider, perhaps with a set time or two for commenting every week. But another would be **expanding my horizons** with what I commented on. Instead of placing certain posts in the 'too hard' basket because the topic wasn't immediately familiar, I could spare a bit of time to try and familiarize myself with at least a couple of them. [our emphasis, score = 3]

The depth and quality of these final reflections matched the depth and quality of student reflections on course content posted to their blogs throughout the semester. Thus, the CLA toolkit appears to be helping to encourage strong students towards reflection about their online behaviour, but is perhaps less successful with students who are weaker or less interested. While it might be argued that the students who agreed to participate in the trials were on the whole more thoughtful or stronger academically, the lecturer of the course argues that this was not necessarily the case. Indeed, some of the participants in the trial were students who were simply more inquisitive, or hoping to "up their grades". At present the sample size of data collected from these trials is too small to make any strong claims, but future work will seek to establish whether student-facing LA is merely useful for piquing the curiosity of students who are already interested in understanding their digital profile, rather than helping students from many different backgrounds and learning dispositions (Deakin Crick, Huang, Ahmed Shafi, & Goldspink, 2015).

Trial 3: IFN614: Information Programs, Semester 2, 2016

Design

The 2016 iteration of IFN614: Information Programs used a similar design as the 2015 version described above. The class website and students' blogs are available at http://2016.informationprograms.info/. However, in the 2016 iteration of the unit, the use of the CLA toolkit was incorporated into the unit design and assessment. A do-analyse-change-reflect pattern was implemented as follows:

1. Do: The blogging assignment was introduced in the first week of semester. Students set up their blogs on the unit site and began completing critical reflection blog posts.
2. Analyse: In week 2 students were introduced to the CoI model (Garrison, 2016) and were encouraged to sign up for the CLA toolkit (optional). Students were required to write a blog post reflecting on the role and activity they were aiming for in relation to the CoI model. This activity was supported by a class run simultaneously on campus and online, which provided an overview of the CoI model and the CLA toolkit.
3. Change: Students were encouraged to think about how they were contributing to the community based on looking at their data in the CLA toolkit dashboard, and to adjust their behaviour if necessary.
4. Reflect: In week 14 students were required to look back over the semester and critically evaluate their engagement in relation to their aims in week 2.

Thus, this trial included a *predict-compare* cycle, where an early phase was coupled with the final reflect cycle. It was hoped that this extra complexity would encourage students to think about how their participation in the online community compared with their desired profile.

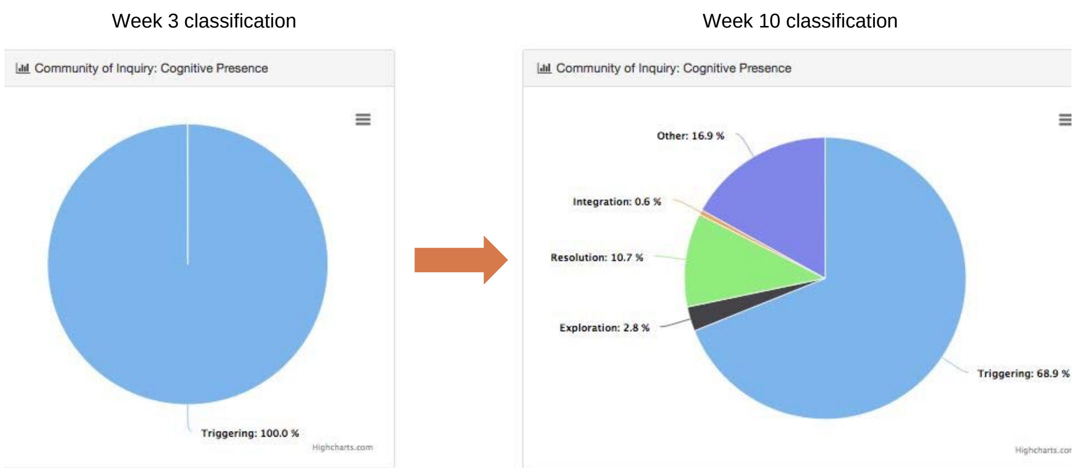

Figure 3. A predict-compare method used in trial 3 was facilitated by a simple automated pie chart that reported upon the varying phases of cognitive presence displayed by students.

Rather than just being asked to write about their participation at the end of the semester, in this trial students were explicitly asked to comment on:

- What role did you want to play in the community this semester? Did you achieve that?
- How many comments you made on your peers' posts?
- Why did you commented as much as you did? what factors influenced the volume of your contributions?
- Did you need to modify your instinctive behaviour to engage the way you wanted to, or felt you should, engage?

Findings

Of the 40 students enrolled in the unit, 23 eventually signed up (thus the participation rate increased to over half the class), which gives us reason to suppose that the tighter (but not essential) coupling of the LA to the assessment task was leading to this stronger participation rate. As per the previous trial, we analysed students' reflections according to their quality. We created a scoring taxonomy similar to trial 2 (Table 4). Eleven students drew on the CLA toolkit in their week 14 post (almost 50% of the trial participants).

Table 4

Quality of students' posts in IFN614

Score	Level of analysis	*N*
1	Included some /all graphs with no reference or analysis	1
2	Included some/all graphs, quantitative analysis relating activity to personality and/or interest	2
3	Included some/all graphs, quantitative analysis relating activity to personality and/or interest, basic analysis on activity in relation to week 2 aim	5
4	Included some/all graphs, referred back to week 2 aim, compared and contrasted, mentioned qualitative aspects	3

We see that of the students making use of LA in their final reflection, more appeared to reach a higher level of quality. The actual quality of reflections using the CLA toolkit as evidence was similar to trial 2, however the requirement to compare aspirations in week 2 with actual behaviour resulted in some sophisticated responses in relation to change over time. For instance, one student mentioned changing her behaviour over the course of the semester:

> In the end, I commented a little more than I created … [CoI piechart], but overall I think I did a good job of making sure I commented meaningfully as the semester wore on. **I made a conscious shift after the first couple of blogs** (and a closer look at the CRA [the criteria sheet for the assignment]!) to move away from generic comments to trying to post links that further explored an element of someone's blog or present some contrary information – I hope that this was well received by my peers. I certainly spent more time on my comments in later weeks than I had in earlier weeks [timeline graph]. [our emphasis, score = 3]

The most sophisticated reflection looked back at the aims for week 2 and the actual pattern of behaviour over the semester in terms of the CoI model:

> In Week 2 I was very aspirational about the role I wanted to play; 'I would like my profile to be professional, respectful, organised, connected and visible. I aim to be an active participant within "reflection and critical discourse that is the core dynamic of a community of inquiry". I achieved my aim of being an active participant as I made over 75 comments on my peers' posts, averaging over 5 per week. **However I feel I did not participate fully in all 4 phases of the cognitive presence in the Practical [sic] Inquiry Model; triggering event, exploration, integration and resolution – despite having sentence openers taped next to my computer**! Triggering events and some exploration were met by sharing an interesting article relevant to a post I had read and also asking some questions, but I felt a lot of my posts were agreeing with and complimenting upon the erudite musings of my peers. I was definitely wary of confronting differing ideas and promoting a critical discourse. **This participation in all cognitive phases needs improving** so the sentence openers will remain up! [our emphasis, score = 4]

In terms of the do-analyse-change-reflect pattern, it was clear that students in trial 3 used the LA provided by the CLA toolkit to help them with the summative aspects of the assessment. This is likely due to the assessment design requiring students to look back over the semester rather than being required to report on their behaviour in an ongoing manner throughout the entire course. While there is no evidence in the reflections to indicate that students used the CLA toolkit to think about how much they had engaged with the course throughout the semester, the teaching staff felt that introducing the CoI framework and the CLA toolkit early in the semester did have an impact on the way students engaged in the online learning community. It helped the students to frame their thinking about engaging in the community early on, and interventions during the semester (an additional class on the CoI and the toolkit as well as blog posts) also reemphasised the importance of thinking critically about engagement using the CoI and the CLA toolkit.

It should also be noted that there were issues with stability of the CLA toolkit in the semester this pattern was implemented, which impacted on student buy-in along with their capacity to access their dashboard.

Discussion

The reported trials record increasingly sophisticated attempts at integrating student-facing LA into learning activities that help students to respond to the assessment structure of a real course. In these cases, the use of the CLA toolkit was optional, and we think it is important that students be given the option of analysing their own behaviour using their own methods. The CLA toolkit is intended to provide formative feedback to students rather than be used in a summative mode, and analytics such as these should be treated with care. As discussed above, advanced analytics such as the cognitive presence classifier will often be wrong when the educational context changes, and students should be given an opportunity to reflect upon, and perhaps challenge analytics reports such as these, rather than be held hostage to them via grading scenarios. However, we can imagine a time when the dashboard is appealing and functional enough to provide students with enough meaningful data on their behaviour, and they will use it without compulsion. After all, many students make use of the analytics provided by games dashboards, or by fitness trackers without compulsion. These tools often provide readily understood metrics in highly attractive dashboards, often about behaviour patterns that are of core interest to students. As student-facing LA matures we anticipate a time where students find the dashboards similarly useful for learning about their own learning processes, and how they might improve them. This imperative becomes even more important when we consider how large institutions like banks, potential employers, and even the government are increasingly using data to classify and categorise both potential and existing employees. It is essential that we equip our students with the capacity to understand how this process might work, where it can be wrong, and how they might challenge and correct this.

The ongoing development of the patterns throughout the three trials points to a difficulty in anticipating how much effort is required to encourage students to utilise student-facing LA. We cannot overstate the importance of tightly integrating student-facing LA into the pedagogical structure of a course. If dashboards are easy to interpret and are useful in helping students to undertake assessment tasks, then they will quickly start to make use of the analytics. But it is rare to see solutions that achieve these two requirements. Our work here is just one step in a series. We consider it essential that ongoing trials and refinements be carried out when working in this area. Had our program of research ended with the first trial then we would have concluded that student-facing LA do not encourage metacognition and reflection. However, this was a failure of LD rather than of the analytics. Using a more sophisticated LD that generated a more obvious coupling to assessment led to more encouraging results. Future work will seek to extend these early indications, helping students to understand how they might use the LA in a more sophisticated way. For example, we can imagine using the scoring rubric and students' responses to create examples to show students how the data in the CLA toolkit might be effectively used as evidence in summative assessment tasks that ask them to reflect upon their participation in online communities of practice.

It is also important to recognise that students might reflect upon and change their behaviour due to other non-LA based interactions that occur throughout a subject. This is not particularly troubling to us. The purpose of student-facing LA is to give students further tools to encourage such changes, but there is no reason why they might not change due to other factors such as an interaction with a classmate. Indeed, the do-analyse-change-reflect pattern does not explicitly require LA. An analyse phase could be encouraged by more than just a dashboard. Thus, there are many ways to learn, but in an increasingly data dominated society it is important that we help our students to understand analytics, and how these might be applied to them in many different facets of their lives once they leave the classroom.

There are some weaknesses in the current implementation of the CLA toolkit which can lead to student frustration and lack of engagement. In particular, the process of registering and then linking up social media accounts for the data scrape can be confusing, and prone to authentication errors if students fail to follow instructions. Some students noticed this, and commented upon problems in their blogs. These real authentication problems are compounded by the current ethics based requirements to show students a full ethical disclosure statement. This statement presents as a wall of text alongside the registration page, and appears to distract students from the instructions associated with registration (where they appear to read neither the ethics statement nor the instructions for registering with the CLA toolkit properly, and merely try entering information causing an error). Current work is seeking to streamline this process.

Our students clearly interpreted some of the reports provided by the CLA toolkit more easily than others. The report that caused the most confusion was the basic cognitive presence report (Figure 3), when it was used without clear reference to the active learning squared pattern. This report only really makes sense if students consider their cognitive presence classification at one point in the class, think about whether they wanted to change it, attempt to modify their behaviour, and then reflected upon how successful (or not) their strategy was at the end of the semester. This LD was not well implemented in the trials which has made it difficult to encourage students towards anything but a superficial understanding. Furthermore, despite constant warning that this report was only an indicative conversation starter, students discussed it as fact in their reflections. They trusted the analytics, and often took them at face value. Few participated in the active learning squared task, but as this task was not clearly linked to assessment this was not particularly surprising. It is important that future work focus upon utilising this pattern in a rich assessment scenario, as this has a very real potential to open up the black box of machine learning in education (Pasquale, 2015), teaching students to question the algorithms that are increasingly being used to classify their behaviour in all aspects of society.

The trials have also revealed wider difficulties with student engagement in the online learning community. For instance, the IAB260 cohort exhibited a low level of engagement across the unit, as well as low use of the CLA toolkit. Indeed, the cohort in general did not produce high quality reflections, a pattern that carried through to this final stage. Two iterations of the unit have found that the students are not active content creators, either in the unit or in their personal lives. Encouraging engagement in the online learning community is a considerable challenge and requires more scaffolding. A more robust implementation of the do-analyse-change-reflect process might assist with this. The WordPress MultiSite installation is effective in providing a blog network that ensures all students' posts are accessible in a single space, however, it is evident that this environment - even with the use of BuddyPress - does not promote informal conversation and sharing, which is critical for establishing a sense of community. With a more integrated implementation of the do-analyse-change-reflect pattern we could imagine more sophisticated behaviour occurring, but at this point there is insufficient data to show this scaffolding will help students to make use of the LA tools in anything but a shallow manner.

Conclusions

Active student participation within the LA cycle is of key importance, and is required to create more sophisticated solutions that utilise LA. This paper has presented two learning design patterns which should facilitate the use of student-facing LA solutions in authentic class based scenarios. Each aims to encourage students towards deeper modes of metacognition and analysis, where they explore data describing their past behaviour patterns and think about how they could change to achieve a data trace that fits more closely with identified goals. The patterns presented here have been applied in a class context using the CLA toolkit, and early results of these trials have been discussed. Future work will continue to refine and develop this approach.

We anticipate that many more patterns are possible, indeed, the predict-compare cycle could be considered a new embryonic pattern for using LA in the classroom. We propose that the LA community create a searchable pattern repository that both learning designers and educators might use as a source of inspiration when creating new course content that makes use of student-facing LA at its core. Such a repository will be more effective if the LD patterns are described using a common format.

Returning to the broader social setting, this paper has proposed some direct solutions for helping people to imagine how LA might be used in a more nuanced manner than the sometimes dominant narrative of "at risk and retention" presupposes. Following these less well-trodden paths will help our students to learn how to learn in a deeper and more thoughtful manner, and to interpret the data and analytics applied to them. We anticipate that both of these skills will become increasingly essential in the coming age of workforce disruption.

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