Incorporating student-facing learning analytics into pedagogical practice

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Despite a narrative that sees Learning Analytics (LA) as a field that enhances student learning, few student-facing solutions have been developed. This is unfortunate, as LA has the potential to be a powerful tool for teaching, in particular by leveraging the possibilities that the quantified self movement offers for encouraging metacognition and reflection. However, a lack of tools exist that enable a sophisticated student focus, and it is difficult for educators to imagine how data can be used in authentic practice. We propose a series of learning design patterns that will help people to incorporate LA into their teaching protocols: *do-analyse-change-reflect*, *active learning squared*, and *group contribution*. We discuss these learning design patterns with reference to a case study provided by the Connected Learning Analytics (CLA) toolkit, demonstrating that student-facing learning analytics is not just a future possibility, but an area that is ripe for further development.

Keywords: learning analytics, dashboards, pedagogy, learning design patterns, CLA toolkit

Learning Analytics for students

Learning Analytics (LA) is a rapidly growing field aimed at understanding and optimising learning and the environments in which it occurs (Long & Siemens, 2011). However, despite a declared interest in analytics *for* the learner, we continue to see solutions that are focussed upon institutions and academics, and in particular the identification of "at risk" students. The 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 can lead to claims that it does not help learning at all (e.g. Bain and Drengenberg, 2016). This is a poor argument to mount; LA has a far richer set of methods, frameworks and tools available, from the automated content analysis of online discourse (Kovanović, Joksimović, Waters, Gašević, Kitto, Hatala, & Siemens, 2016), to social learning analytics (Buckingham Shum & Ferguson, 2012), and multimodal methods (Blikstein, 2013). 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.

Despite this growing breadth, the field has placed surprisingly little emphasis upon the learner. This is unfortunate, for a number of reasons:

- Ethically, we consider it problematic to collect data about a person without giving them an opportunity to access that data, examine it, and perhaps to make use of it in their own ways.
- From a sensemaking and interpretational perspective, it is far easier for the person who generated a datapoint to understand what it means. For example, the student who drops out of a MOOC could have done so for a number of reasons: they may have enrolled for mere curiosity; they might have learned the one specific thing that they enrolled to learn; perhaps the teaching mode was terrible and they decided to leave; or perhaps they just got busy at work. Only that individual will know why they left, and be able to interpret the digital traces (Latour, Jensen, Venturini, Grauwin, & Boullier, 2012) with reference to their life situation. Importantly, these traces can often be understood in a far more nuanced manner than "big data" which hides the specifics of subgroups and behaviours in averages that generate an idealised norm. However, sensemaking requires far more care than merely providing students with a dashboard that has "wow" factor (Duval, 2011).
- The opportunities afforded by LA for encouraging metacognition and reflection will only eventuate if learners are given pedagogically relevant access to reports and data about their learning. In the coming forecasted age of workforce disruption (CEDA, 2015) it will become increasingly important that we train our students to think about data, reflect upon its meaning and then act. What better data source to maintain their interest than their own behaviour? The lessons of the quantified self movement could be put to good use, and significantly extended for the case of learning (Duval, 2011; Lee, 2013).

However, there are reasons to be careful. In particular, there are important ethical considerations in relation to providing analytics to learners. For example, what might be the expected response of a first in family student who is informed that they have been classified as “at risk” by a LA system? We consider it highly likely that such a student would believe the classification of the LA system, rather than fighting back and changing their behaviour. Thus, the failure of the student would be in no small part *generated* by the system. 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). However, as raised by Slade and Prinsloo (2013), *not* acting upon information about the predicted failure of a student can also be seen as highly unethical; in an increasingly fee driven system they are likely to be wasting large sums of money on a course of study where they are not likely to succeed.

Thus, we consider it essential that both learning analytics practitioners and learning designers start to develop and explore new ways in which learner centred LA can be authentically incorporated into pedagogical practice. But why has so little emphasis been placed upon the learner in relation to systemic institutional adoption of LA?

What is going wrong?

The institutional adoption of LA in higher education can only be considered sporadic at best (Siemens, Dawson & Lynch, 2013; Colvin, Rogers, et al. 2015; Sclater, Peasgood & Mullan, 2016). It seems likely that one of the reasons for this lack of uptake lies in the difficulty in imagining how LA might be used at a small scale. That is, how can LA solutions be adapted by practitioners in learning designs (LDs) fit for the classroom?

It is often difficult for educators to imagine how students might use educational data. Verbert, Duval, Klerkx, Govaerts and Santos (2013) have suggested a learning analytics process model that considers four stages: *awareness, reflection, sensemaking,* 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 relatively easy to motivate student facing dashboards in a class that uses reflective practice, few sophisticated paradigms have been developed, and other scenarios are harder to imagine. There is a tendency for studies to show students a dashboard and to perhaps then conduct interviews or surveys to explore usage. Few people have tried to develop more sophisticated pedagogical models from these dashboards.

This problem is compounded by an interdisciplinary gap between computer scientists and educationalists. Many of the people that would be most interested in exploring novel ways in which LA might be incorporated into learning designs do not have the programming skills necessary for developing their own technologies. This leaves them hostage to vendor provided solutions. Even more problematic, a lack of awareness about the wide variety of ways in which data can be analysed and represented means that they often underestimate the abilities of data science and what it might be able to achieve.

Strategies for Building Learner Centred LA into Learning Design

Despite the problems identified above, student facing LA solutions are both possible, and gaining in sophistication. Firstly, there is reason to believe that students can understand data about their learning processes (Corrin & de Barba, 2014). A second study (Kahn & Pardo, 2016) exploring the use of student facing dashboards that summarise weekly engagement with course materials has shown indications of a quick burn in period, after which students tend to check back on a weekly basis to ensure that they are keeping “on track”. This behaviour pattern suggests that students can learn to interpret and understand some analytics dashboards, and we might expect that these capabilities will improve with practice.

However, the bulk of pre-existing work appears to consist 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 new found knowledge. Lockyer, Heathcote and Dawson (2013) have introduced a 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, a form of *process analytics* provides insight into learner information and knowledge processing within a set of tasks. In this case, 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.

How can we extend these early indications of potential success? Moving forward will require a series of technology enhanced learning (TEL) design patterns (Dalziel, 2014; Goodyear & Retalis, 2010) that make use of LA at their core. In what follows, we sketch out a series of LA patterns, and an early case study where they have been tested using the Connected Learning Analytics (CLA) toolkit (Kitto, Cross, Waters & Lupton, 2015).

Do-analyse-change-reflect

One obvious strategy for using student facing LA in a class context involves the following sequence:

1. **Do:** Students are instructed to participate in some sort of activity. Perhaps they should prepare for a flipped class by watching videos, maybe they need to write a blog post and then comment on 3 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, mobile apps, and online games all provide examples of tools that might be used to collect such data.
2. **Analyse:** Students are encouraged to consider LA dashboards that result from the *do* phase. Reports and tools from the 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 LA pattern 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 this final stage to be essential to the effective implementation of this LA pattern. An all too common scenario in LA implementations that have a student focus typically involves students being shown a dashboard, being interested in it, but then failing to consider what it means *to them* (Verbert, Duval, et al., 2013). It is important that the *change* phase be driven by a *reflect* phase to encourage students to 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 new things out, without fear that this would affect their final grade. However, we can imagine that other options might arise in specific circumstances.

We consider this design to be one of the core patterns that can be used to incorporate LA into learning activities. Each of the patterns that follow make use of this core sequence. The fundamental nature of this pattern stems from the core question that it asks students to consider, which could be summarised as: Are my self-perceptions reflected in my profile? How might we encourage students to ask this question? Perhaps students could consider an activity dashboard that shows them how much time they are spending in class activities compared to the rest of their cohort, as implemented in a study by Khan and Pardo (2016). Interestingly, the lack of the final *reflect* phase in that study means that students are unlikely to be motivated to *change* their behaviour as the learning design remained in the *do-analyse* phases. A full implementation of the above pattern would require an extension of that learning design where students are required to complete a critical analysis of their behaviour throughout the semester. This leads us to introduce the case study that we will draw upon for examples throughout the remainder of this paper.

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

The Connected Learning Analytics (CLA) toolkit (Kitto, Cross, Waters, Lupton, 2015), has been designed to enable those educators who are teaching "in the wild" using standard social media, to utilise the benefits of Learning Analytics. 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 harvest has been implemented for Twitter, Facebook, WordPress, Youtube comments, Trello and Github. Contextualised activity, social network, and content analysis reports are available for instructors, with a student facing dashboard giving individual students access to amalgamated reports about their participation in learning activities that make use of the CLA toolkit.

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). However, two iterations of class trials have inspired the three patterns discussed in this paper, along with a number of results about the usability of the current interface. In what follows, we will interlace the description of our LD patterns with reference to this particular tool.

In this section we consider data from trials with two example cohorts. In each case the same instructor (KD) coordinated the unit using her own WordPress installs, rather than the Blackboard LMS environment that is the standard offer at the university. A few key differences between the two units are worth noting:

- **IFN614: Information Programs**
  Design: This 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. The site is available at http://2015.informationprograms.info. Students each had their own personal forum on the site where they posted their weekly activities, and could use the forums to ask questions about assessment and unit content.
  Assessment: A blogging assignment worth 50% of their final grade required students to post critical reflection activities weekly on their personal blogs. Posts covered a range of topics related to unit content. Blog posts comprised 40% of their grade. The blogging assignment also required them to actively contribute to the learning community by commenting on their peer's forum posts, engaging in discussion using the social functionality on the site including the forums, or using social media like Twitter with the unit hashtag. Engagement in the learning community contributed to 10% of the student's final grade.
  CLA toolkit: 33 students enrolled in this offering of the unit, and 12 signed up for the trial discussed here.
- **IAB260: Social Technologies**
  Design: This 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 worth 50% of their final grade required students to post critical reflection activities weekly on their personal blogs. Posts covered a range of topics related to unit content. They 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 grade. Active contribution to the learning community was worth 10% of the grade. This included commenting on peer's blog posts, engaging in discussion using the social functionality on the site, or using social media like Twitter with the unit hashtag.
  CLA toolkit: 68 students enrolled in IAB260, and 24 students participated in the trial discussed below.

The Toolkit was implemented in IFN614 Information Programs in Semester 2, 2015, without being integrated into the assessment design. Students were invited to sign up in Week 8 via a post on the unit site (http://2015.informationprograms.info/learning-materials/week-8-planning-managing-and-evaluating-programs-products-and-services/). Recruitment focused on piquing students' curiosity and played on their interest in data and classification. Students were not clear on what they should do with the toolkit but were still interested in signing up and having a look at their data in the dashboard. However, the LA offered by the CLA toolkit lacked a clear assessment driven purpose and it is not clear whether usage impacted on students' learning.

Following this initial trial, the *do-analyse-change-reflect* pattern was designed and recently implemented with the IAB260 cohort. The trial proceeded 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 (http://2016.socialtechnologi.es/administration/the-connected-learning-analytics-toolkit/), however, take up was initially very low. In Week 9, the unit content focused on quantified and connected lives, and in the context of exploring the quantified self movement. An in class workshop was run (by KK) 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 very low (eight 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. There was no observable change in student behaviour.
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 write this reflection. Some students did use the CLA toolkit to prompt their reflections, however, their use of the data was primarily descriptive. They tended to quantify their contribution to the community in terms of number of posts and comments.

This cohort exhibited a low level of engagement across the unit, as well as low use of the CLA toolkit. Indeed, the cohort did not in general produce high quality reflections, a pattern that carried through to this final stage. Two iterations of the unit have found that the cohort 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 in this unit and it 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 do not at this point have data to show that this scaffolding will help students to to make use of the LA tools in anything but a shallow manner.

One example of the difficulty surrounding student interpretation of data involves a CLA toolkit dashboard that gives a simple classification of the cognitive presence displayed by that student within their community of inquiry (Garrison, Anderson & Archer, 2000). We are yet to see any students blog about this report, which suggests that they do not understand what it means. We could imagine a *do-analyse-change-reflect* cycle where a student considered their cognitive presence classification at one point in the class, thought about whether they wanted to change it, attempted to modify their behaviour, and then reflected upon how successful (or not) their strategy was at the end of the semester (see Figure 1). However, it has been difficult to encourage students towards anything but a superficial understanding of this educational construct in the two trials run to date. In both cases students were invited to examine their dashboard, but little scaffolding was given to really help them understand what it meant, and more importantly, to reinforce that understanding in a later task. A new trial is currently in progress with the 2016 IFN614 cohort that used a lecture at week 2 to introduce the concept of a Community of Inquiry (Garrison, Anderson & Archer, 2000) and give students the tools they need to understand the cognitive presence report (*do-analyse*) and to then keep using this information throughout the semester (*change*), before incorporating what they have learned into their later assessment (*reflect)*. This process will be further facilitated by incorporating the active learning squared pattern that we will now discuss.

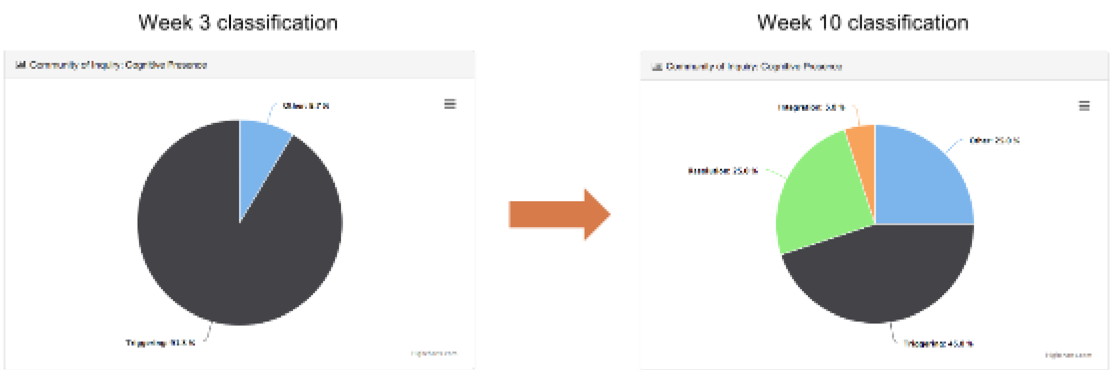

Figure 1: Viewing an early classification of their cognitive presence in an *analyse* phase might lead to a student deciding to *change* their behaviour. This decision and the new strategy could then be discussed in the *reflect* phase.

Active Learning Squared

The cognitive presence report discussed with reference to the *do-analyse-change-reflect* pattern can be used in a more pedagogically sophisticated manner with a very simple extension that is grounded in modern machine learning techniques. In this case, a classifier assists students during their *analyse* phase, by telling them how specific posts have been classified, and asking them to correct it if they think the classification is wrong. This provides the scaffolding that appears to be essential in encouraging students towards deeper metacognition.

The *active learning squared* pattern arose from a the problem that classifiers are never perfectly accurate, which makes it difficult to justify using them in an educational setting where poor classifications can lead to adverse student outcomes. For example, in an adaptive learning system, a student might be forced to repeat a series of exercises that they have already mastered, or they might be classified as “at risk” and might receive ongoing recommendations about extra support services that they should access (but do not actually need). The pattern mitigates this problem by placing the student in this classification loop. Giving students an opportunity to to consider the way in which their behaviour has been classified and to correct the classifications if they think they are incorrect 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 runs as follows:
1. **Do-analyse-change-reflect:** Students participate in 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 in a class that emerged during the first phase. This step does not include student action but is essential to the *active learning squared* pattern, which requires that the student correct the machine learning output.
3. **Examine:** Students are shown a dashboard that shows how their aggregated behaviour in the *do* phase has been classified. They are informed that the classifications could be incorrect, and that they should carefully consider what the dashboard tells them in the light of how they think they are behaving.
4. **Relabel:** An extension of the dashboard enables students to unpack the black box of machine learning and to understand how they have been classified. They are encouraged to use this dashboard to view the way in which their individual behaviours were classified and to relabel them if they think that the classification is incorrect. The current dashboard allows students to add a free text justification of their relabelling and to highlight features that they think contribute to it.

This pattern both encourages students towards metacognition, and sidesteps an ongoing problem with accuracy and lack of portability of machine learning methods for the purposes of education. For example, the current best performing classifier of cognitive presence (Kovanović, Joksimović, Waters, et al., 2016) was trained and tested upon one specific data set (computer science classes using Moodle, in a Canadian University.) It has not yet been tested upon a different data set, as no alternative labelled and sharable datasets are currently available. However, we think it reasonable to suppose that the accuracy of this classifier will decrease when it is used on data collected in another context (e.g. a data set that was gathered in Australia from student interactions in the Wordpress installation used for IAB260 and IFN614). Rather than ever better classifiers, we have been following an alternative avenue by considering whether it is possible to improve the educational data sets that train them. One way to achieve this would involve the rapid collection of new data that is contextualised to a specific class context using the *active learning squared* pattern.

To test this idea, we have run a short trial with the IFN614 cohort described above. The CLA toolkit currently has a simple Naive Bayes cognitive presence classifier that was trained upon the Canadian data set. As such, it is not the state of the art (Kovanović, Joksimović, Waters, et al., 2016) and is not expected to be terribly accurate. It has been used in trials merely to explore the potential of using this dashboard with students. In the 2015 IFN614 trial, a simple interface was created which invited students who were using the toolkit to *examine* the classifications that it had given their posts, and to *relabel* them if they thought them incorrect. Students who had signed up to the CLA toolkit were notified about the new active learning functionality with only one week to engage with this feature in a small pilot study. In total, 6 students trialled this functionality (a 50% participation rate for those students using the CLA toolkit). A total of 64 posts were examined and classified by six students, out of a possible total of 34 enrolled in the class, 12 of whom had signed up to the trial. Table 1 provides a confusion matrix that allows us to explore the relative accuracy of the students in the trial, and the classifier with reference to the expert coder. The accuracy between the student classifications and the expert coder was low 43.05% (kappa=0.256) but was much lower for the classifier which achieved an accuracy of 25% for this trial (kappa=-0.013). We can see that the students achieved better accuracy than the classifier, which suggests that the *active learning squared* pattern shows promise for use in the classroom.

Table1: A confusion matrix for the 2015 IFN615 *active learning squared* trial. The hand coder provides an assumed ground truth, and is compared to both student and ML classifications of behaviour. We see that the students achieved greater accuracy than the ML, suggesting that the *active learning squared* pattern can be successfully used in a class context.

		Students/NB classifier					Recall
		Triggering	Exploration	Integration	Resolution	Other	
Coder - Assumed Ground Truth	Triggering	18/18	1/1	0/0	0/0	0/0	0.947/0.947
	Exploration	1/8	7/0	1/1	0	0	0.538/0
	Integration	4/8	3/0	2/0	0/0	0/1	0.222/0
	Resolution	4/8	3/0	2/0	0/0	0/1	0/0
	Other	12/18	4/4	0/0	2/0	4/0	0.182/0
Precision		0.461/0.30	0.38/0	0.4/0	0/0	0.5/0	

More work is required to further develop this pattern, and a second, more extensive trial is currently underway with the 2016 IFN614 cohort. This study will be discussed in more detail in a future paper. We will now move onto a discussion of our final pattern, which is currently being developed and trialled in two other classes.

Group contribution

Group work is an ongoing source of frustration for both students and academics at many universities. There are many ways in which a team can fail to work well together: communication may lapse; or a lack of trust may mean that only one sub group completes all of the assessable work; perhaps the team is a group of ‘leaders’ all trying to head in their own direction. Sometimes an individual student might not be aware of their teammate’s dissatisfaction until it is too late in the semester to adjust their performance. In large classes the teaching team often finds out when it is too late to help the group resolve its issues. How might a LD pattern be created where LA is used to inform students about their participation in teams? We propose the following sequence of steps:

1. **Nominate Forums:** Team members start by discussing what tools they are going to use to manage a project, and how these will be used. They then link those tools to a data harvest tool (perhaps the CLA toolkit, but other data sources could be used instead, e.g. Google Analytics).
2. **Do-analyse-change-reflect:** Students then enter a cycle where they continue with their group work project. However, care should be taken to ensure that students are critically analysing their contribution to the team, and adjusting their behaviour accordingly. They could write a weekly journal entry discussing what is going on, what the data tells them and how they propose to change their behaviour. They might have a conversation with their team at the start of each meeting about what the data reveals and provide a progress report to their teacher. The reflect phase during this part of the pattern should be formative rather than summative in order to encourage experimentation among students as they try out new strategies for managing group dynamics.
3. **Report:** Finally, individual students would report upon their contribution to the team in a summative assessment item. They should be required to make use of data from their LA dashboard to argue the case about what they have contributed to the project deliverables and what they have learned about group work in the process of producing them (referencing material from the *reflect* phase of stage 2).

At present the CLA toolkit has a partial implementation of the functionality required to implement a study of this type. One particular difficulty arises with the APIs that are currently publicly available: for example, Google+ data is difficult to access with the API unless a group has been constructed via the Google Apps extension. This ‘feature’ tends to rule out the educators that the CLA toolkit is explicitly trying to assist (i.e. those that “teach in the wild” without institutional support). Solutions are available if teaching teams move to other social networks (e.g. the Facebook API does not currently suffer from a similar restriction) but they often feel that doing so would impoverish the learning experience with no immediate benefit to the students. Without an opening of the APIs for use in these types of educational scenarios the CLA toolkit will not be able to assist with the collection of analytics data to enable teaching and learning. *Data access* is increasingly becoming key to a large number of decisions and it is important that educational institutions directly confront the issues associated with access to data that they (or their students) generate (Kitto, 2015).

How might we imagine the *group contribution* pattern being applied given the current functionality of the toolkit? Using the CLA toolkit would allow students to sign up to data collection for the relevant environments where they are carrying out their learning activities. They might declare that they would communicate about the project in Facebook, manage deliverable dates and tasks in Trello, and submit code using a project page on GitHub. If all team members signed up to data collection for these three environments, then the data for the relevant FB group, Trello board and GitHub project would be collected (and no more - which respects privacy). A new dashboard would have to be incorporated into the CLA toolkit to help students to track their group work participation. This is a current project, and the planned wireframe has the layout shown in Figure 2. In this dashboard all group members would be given access to a group dashboard, where they would see both a relative activity count (in the form of a bar chart representing contribution to group processes for each media that they had agreed upon using in their project), and measures that they could use to explore the *quality* of those contributions. For the scenario discussed here we would anticipate using metrics such as:

- A cognitive presence classification to help students understand how much of their behaviour in Facebook was contributing to the group and its assigned inquiry based task.
- A count of tasks responsible for (R) vs tasks resolved (F) in Trello
- A measure of lines of code (LOC) modified in the Github site (to extend information provided by the bar chart which would just summarise how many commits have been made by that team member).

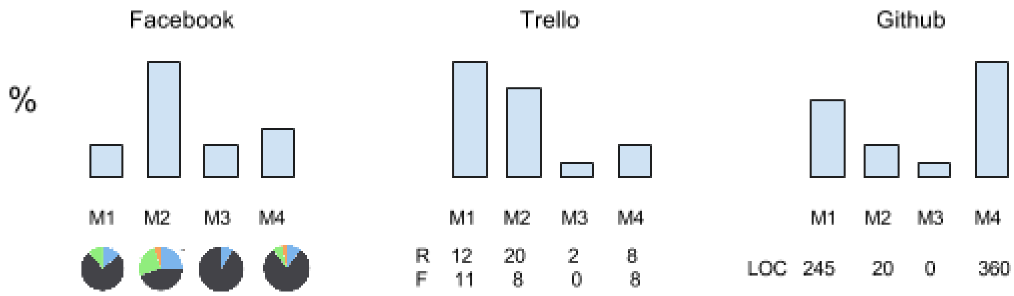

Figure 2: A proposed wireframe for the CLA toolkit groupwork dashboard. Relative activity levels in different social media are illustrated, along with media specific data that helps students to consider the *quality* of their contributions to the project (not just their quantity).

Considering just this simple collection of information it is possible to form hypotheses that might be discussed by the group, or chased up by a teaching team. For example, referring to Figure 2, we can see that group member M3 is perhaps not contributing to either the group processes (i.e. project management in Facebook and Trello) or the final product (i.e. code contributions on Github). Should their participation be marked down? It may be that they are contributing in another way not captured by the data (perhaps they are performing a vital role in face to face group discussions). Perhaps they are just having a very busy week with another assessment in a different unit. It is important that they be given a chance to reflect and respond to this data pattern, rather than be automatically assessed according to what is likely to be only a partial data trace. Similarly, students may be rotating roles, which would result in changes to their project management vs content delivery type behaviours. Dashboards should allow for a drilling down to specific date periods to facilitate the exploration of patterns such as these. Khan and Pardo (2016) have also demonstrated that a weekly reset of activity data in student facing dashboards is a powerful mechanism for motivating students who may be falling behind (as they can always perform better next week) as well as ensuring that those who perform well one week are less motivated to “slack off” and coast along after discovering that their contribution is far greater than the rest of their cohort. The utility of different data representations and resets will be explored in a future trial.

Dashboards such as these will give students the opportunity to develop both their data literacy, and their ability to think about and analyse their contributions to team based work. This will not only provide them with essential future workforce skills but will encourage them to change poor group based behaviour patterns before it is too late and they have let their team down or obtained an unsatisfactory grade.

Conclusions and Future Directions

Active student participation within the learning analytics cycle is of key importance, and it is required to create more sophisticated solutions that utilise LA. This paper has presented three learning design patterns which should facilitate the use of student facing LA solutions in class based scenarios. Each aims to encourage students towards deeper modes of metacognition and analysis, where they explore the data about their current behaviour and think about how they could change to achieve a data trace that fits more closely with identified goals. Two of the patterns presented here have already 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 these patterns.

We anticipate that far more than these three patterns are possible, and propose that the LA community create a pattern repository that might be used as a source of inspiration by both learning designers and educators when creating new course content. Future work will seek to establish a common format for describing these patterns, as well as a trusted and searchable repository where they can be both collected and found.

In the broader social setting, a number of popular claims have been emerging recently that learning analytics does not help student learning (e.g. Bain and Drengenberg, 2016; Ruggiero, 2016). Many of these discussions assume that LA is merely about collecting click stream data and using it to predict student success. It also assumes that students will not be involved in interpreting the data traces that they leave in our educational systems. This paper has proposed some direct solutions for helping people to imagine how LA might be used in a more nuanced manner, directly with students. Doing so will help our students to learn how to learn in a deeper and more thoughtful manner, an essential skill in the coming age of workforce disruption.

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