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Data Analytics in Citizen Cyberscience: Evaluating Participant Learning and Engagement with Analytics

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ABSTRACT

Citizen Cyberscience (CCS) projects are online projects that engage participants with no necessary prior scientific experience in online tasks of very varied types and that contribute to the scientific research in different domains. Many research studies confirm the usefulness of CCS projects to researchers while less has been done to explore their added-value for the participants. Specifically, we are interested to know to what extent CCS projects help participants learn while participating through typically small-sized and very specific tasks.

We propose in this work to include another source of quantitative data to the research toolbox usually used to evaluate learning in informal learning contexts as the one of citizen science. This data source is learning analytics that makes use of the already very ubiquitous web analytics and that is heavily used in varied online learning environments. Based on our experimentations with two CCS pilot projects, we created a framework to help CCS project designers properly implement learning analytics in their project in order to make the full use of these analytics and integrate them with other sources of quantitative data related to the user experience. We apply the proposed framework to explore the interaction between learning and engagement in two pilot CCS projects of different types: volunteer thinking and gaming. Based on our experience, we conclude with few good practices and recommendations to avoid pitfalls.

1. INTRODUCTION

Citizen science refers to collaborative projects where researchers invite volunteers and engage them in scientific activities that they don't necessarily have any initial experience in (Hand, 2010). Volunteers are typically asked to perform data collection and processing or monitoring activities. The generalization of the interactive web2.0 in the last decade allowed for the development of Citizen CyberScience projects (CCS) that engage participants in tasks which also involve the use of computers and the internet. Some of these multi-disciplinary projects underlying online crowd-powered systems are also addressed as Human Computation. They solicit the human cognition to achieve new capabilities beyond computer capabilities (Michelucci, 2013).

Crowd-powered science has demonstrated its usefulness for research (Sauermann & Franzoni, 2015); however, little is known about its potential for volunteers. Specifically, we are interested in understanding how citizens learn from "virtually" participating in projects, and what they do learn.

The educational impact of citizen science is already addressed by several studies (Bonney, Phillips, Ballard, & Enck, 2015); (Cronje, Rohlinger, Crall, & Newman, 2011); (Crall, Jordan, Holfelder, & al., 2013)). Nevertheless, results on learning in citizen science focus on effects of participation on scientific literacy and on content-knowledge (Jordan, Ballard, & Phillips, 2012). Our perception of learning in CCS projects is instead multidimensional and is not limited to the scientific literacy (see discussion below in subsection 1.1), hence we need adapted evaluation tools to assess the different dimensions of the impact of CCS on the learning of the participants.

Increasingly data analytics appears to provide such an evaluation tool as it involves tracking the online actions of participants through time in order to reveal potential trends or user profiles, to analyse the effects of certain decisions or events, or to evaluate the performance of a given tool or scenario.

Globally, managers and decision makers agree on the "the importance of increasing the use of analytics in decision making" (Kiron, Prentice, & Ferguson, 2014), and as analytics is becoming ubiquitous in online activities, it appeared natural to use it in education in general (Siemens & Long, 2011) and to study learning in citizen science projects too as they also offer a learning experience to their participants. Hence we have made learning analytics a core tool in our toolbox for evaluating learning in the pilot projects that are developed as part of the European project Citizen Cyberlab.

This paper aims to present a framework that establishes learning analytics in a given CCS project on the basis of the expected learning outcomes of the project. The analytics data are collected and then aggregated into indicators reflecting the effective achievement of the learning outcomes of each participant. We don't discuss here the technical details of implementing and collecting analytics events. Our partners at the Citizen Cyber Lab developed for this purpose a monitoring framework: the CCLTracker presented in detail in (Fernandez-Marquez, et al., 2016). Nevertheless, our framework is independent of the analytics data collection method.

Our framework is applied to two pilot projects, a volunteer thinking application and a game. GeoTag-X[1] is a pilot crowdsourcing platform launched by The UN Institute UNITAR/UNOSAT to rely on human computation to support disaster response. The primary aim of GeoTag-X is to develop an application that facilitates the human harvesting and analysis of photos related to disasters around the world such as floods, drought, and war destruction, and the creation of datasets that could be used by humanitarian organizations in their response. In order to be successful in this aim, the project worked on the transfer of the expertise from knowledgeable individuals to the crowd. Specifically, the target skills are: to identify relevant photos, to conduct detailed analysis of those photos and potentially geo-reference them as precisely as possible.

The second pilot project is of a completely different nature and different target participants. It is an interactive educational learning game called Virtual Atom Smasher (VAS[2]), developed by CERN, The European Organization for Nuclear Research. In this game, the players are challenged to “tune” a simulation of high-energy particle collisions to give an optimal description of a chosen set of reference data, while simultaneously learning about particle physics.

We share here our experience and make few recommendations to help other CCS project designers who plan to include learning analytics in their evaluation toolbox. In fact, nearly two decades of research in educational data mining (Romero & Ventura, 2010) demonstrates that designing systems that provide the right data and extracting useful information from large amounts of data are not trivial tasks. Also, Analytics data should be triangulated with psychometric data (quizzes and surveys) which opens a large avenue for further research.

It should be kept in mind that our framework was applied to pilot projects that availed limited datasets. The data was collected during short periods of time and with a small number of participants. Hence, the statistical analysis options were limited. The purpose of the article is not to introduce new statistical analysis methods of analytics data neither to present novel analysis results, but rather to share our experience of defining and using learning analytics in assessing learning and engagement in CCS projects. As a proof of concept, we conducted a small typology analysis that revealed interesting patterns in the profiles of the participants, and that would be interesting to explore in other CCS projects with richer analytics datasets.

We continue our introduction with a presentation of our understanding of learning and engagement in CCS projects and with a brief introduction of learning analytics. Section 2 summarizes the different analytics of interest that could be generated and tracked in citizen

[1] http://GeoTag-X.org/
[2] http://test4theory.cern.ch/vas/

science projects. We then proceed in section 2.2 with the specific task of using learning analytics to understand which types of learning occur when participating in online citizen science activities. We present in section 3 an example of application where we analyse the profiles of the participants in a pilot project, as revealed by the analytics data. Finally, we conclude with a synthesis of the good practices learned from our experience and suggest future developments.

1.1 Learning in Citizen Cyberscience

Similarly to formal learning contexts where learning is the result of the interactions of the learner with content, with instructors and tutors, and/or with other learners (Elias, 2011), learning in citizen science happens through activities and potentially from interaction with peers and experts.

Wiggins and Crowston (Wiggins & Crowston, 2011) describe citizen science as a type of collaboration where individuals are involved with the scientific community in research projects addressing issues from the real world or more generally ones that might interest non-specialists. Citizens and scientists work collectively to achieve a common goal, usually in the form of data collection or social action.

While the contribution of volunteers to scientific data collection and analysis has been well documented, understanding how participation in citizen science projects affects learning is at the heart of many studies (Schneider, DaCosta, Abu-Amsha, Jennett, & Kloetzer, 2016) (Kloetzer, Schneider, & da Costa, 2016) (Crall, Jordan, Holfelder, & al., 2013), (Cronje, Rohlinger, Crall, & Newman, 2011), (Jordan, Gray, Howe, Brooks, & Ehrenfeld, 2011) and the evaluation of learning outcomes of citizen science projects is increasingly gaining interest (Jordan, Ballard, & Phillips, 2012).

Learning outcomes in citizen science can in general be defined on multiple levels. There are individual-, program-, and even in some programs, community-level outcomes (Jordan, Ballard, & Phillips, 2012). There is also a balance to be clearly defined between learning goals and scientific goals (see discussion in (Lieberoth, 2014)). We focus in this work on the individual outcomes that are tightly linked to the learning induced by the participation.

Evidence of impact on scientific literacy and on content-knowledge is the most discussed (Jordan, Gray, Howe, Brooks, & Ehrenfeld, 2011). A recent large-scale survey was conducted to assess the different dimension of learning through participation in CCS projects (Schneider, DaCosta, Abu-Amsha, Jennett, & Kloetzer, 2016). Abide from this cross-projects study, researchers usually assess learning in citizen science with evaluation tools that are specifically designed to capture the specific nature and content of one project, which makes difficult the comparison between different projects performance.

One of the objectives of our work presented here is to set up a common framework where learning in different citizen science projects can be assessed using the same approach while adapting the tools to the context.

Preliminary research during the Citizen Cyberlab project (Kloetzer L. , et al., 2013), revealed that learning in CCS projects occurs in multiple directions. Interview data indicated the existence of six categories of learning outcomes: At the task level, we distinguish learning regarding the project mechanics and pattern recognition skills. At the higher project level, we can distinguish scientific topic learning and general scientific literacy. These types of learning are encouraged in the context of the project but they are usually acquired by additional involvement in the project community. Finally, the interviews revealed the potential acquisition of off-topic (e.g. communication skills, computer literacy) and personal development skills that cover a wide range of skills with no relation to the CCS project domain or type. They are in fact fortuitous outputs induced by heavy involvement in the projects.

Traditionally, assessing citizen science projects impacts relies on pre- and post-tests and responses from surveys, interviews, and board diaries (e.g. (Brossard, Lewenstein, & Bonney, 2005) (Jordan, Gray, Howe, Brooks, & Ehrenfeld, 2011)). Tracking the achievement of individual participants can also be done through activity logging. This article will emphasize the use of logging capabilities offered by the modern analytics frameworks to specifically evaluate the learning of participants in CCS projects.

1.2 Engagement in Citizen Cyberscience

Meece & al. (Meece, Blumenfeld, & Hoyle, 1988) set a model for cognitive engagement in the classroom. Engagement from an educational point of view is seen as learner participation, and interaction with the learning material, learning activities, and the learning community.

O'Brien and Toms (O'Brien & Toms, 2008) proposed a conceptual framework for user-engagement with technology that could be used in various application areas, including technology-based learning, citizen cyberscience projects, etc. According to O'Brien & Toms, "**Engagement** is a quality of user experiences with technology that is characterized by challenge, aesthetic and sensory appeal, feedback, novelty, interactivity, perceived control and time, awareness, motivation, interest, and affect". The resulting conceptual model of engagement distinguishes 4 possible phases through an engagement process: The user initiates and sustains engagement during a session; he disengages, and potentially reengages several times during a single interaction with the system or through subsequent sessions. O'Brien & Toms also considered the factors that usually lead to non-engagement, where the user completely drops the interaction with the system.

Since learning and engagement are closely interrelated, the framework proposed here will also address the engagement of the participants in CCS projects. Well-designed analytics will allow for a better understanding of their interactions.

1.3 Learning Analytics

With the generalization of technology-based learning opportunities, and with the generalization of data science practices in increasing number of fields and domains, it was natural to see a rising interest in the collection and the exploitation of educational analytics for various purposes: educational, academic (administrative) and even economic and strategic (Ferguson, 2012). According to the 1st International Conference on Learning Analytics and Knowledge[3], "Learning analytics deals with the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs".

Learning analytics finds its immediate legitimacy in the contexts of online education, in Virtual learning Environments (VLEs) and in massively open-access online courses (MOOCs) for formal or informal learning. It is used to support the provision of a timely picture of the learning process of theoretically every learner, allowing for appropriate adjustments and feedbacks and overcoming the usual delays that educational systems usually suffer from. As an example of the application of learning analytics, Morris, Finnegan & Wu (Morris, Finnegan, & Wu, 2005) studied the impact of student engagement on their success in a fully online asynchronous program. They tracked student basic activities related to the participation on a Learning Management System (LMS) (e.g., content pages viewed, number of posts) as well as the duration of participation (e.g., hours spent viewing discussion pages and content) and they were able to discriminate significantly between "withdrawers" and "successful and unsuccessful completers".

Similar practices seem adapted to citizen cyberscience projects. As we discussed earlier, online behavior of participants has undeniable effects on learning in citizen science projects. There are also similar concepts of engagement, hence tracking the digital traces of the participants in citizen science projects with learning analytics may provide an extra means to understand their behavior and enhance their experience. Besides, issues regarding the CCS web site usability can also be detected with analytics. Although these applications of analytics are very important, they fall outside the scope of this article.

In addition, analytics allows for a fine-grained engagement analysis. If the analytics are well designed, an engagement study could be easily scalable, i.e. we can study engagement globally, on a daily basis, or even hourly if it is needed, provided, again, that the number of users is sufficiently high to generate meaningful statistics. Also, with the possibility of observing the user

[3] https://tekri.athabascau.ca/analytics/

behavior in a nearly real-time manner, it is easier to detect unexpected behaviors, detect potential usability issues and make timely actions to improve pilot projects faster. User profiling/segmentation is also possible with analytics and can help to develop and assess specific actions for engaging under-represented and specifically targeted groups.

We used analytics as one part of a larger evaluation toolbox for assessing learning and engagement in CCS. Alongside the data-driven approach of analytics, we deploy other traditionally used tools such as online surveys, on-topic quizzes, diary analysis, and structured interviews with active participants and even behavioral observations and focus groups run during outreach events. In fact, learning induced by social and collaborative activities seems to be the most effective in the context of CS (Kloetzer L. , et al., 2013). This type of learning is not easily tracked with learning analytics, hence, analytics could be combined with online surveys and quizzes. While surveys might be subjective and respondent samples not really random, analytics could lack accuracy but would still be automatically collected for virtually every user. Merging mutiple sources of data—surveys, quizzes and analytics—promises to lead to a better analysis as long as there is enough participation.

Existing learning analytics data collection tools

The use of learning analytics to inform data driven decisions is expanding in formal education institutions, hence most of the Learning management systems and MOOC platforms also offer built-in analytics tools. Game sites can now also use analytics tools available from game platforms such as the open source game analytics tool RedMetrics (Himmelstein, Goujet, & Lindner, 2016), or the one offered by Unity[4] and used for example to track the educational games developed at Aarhus University in Denmark: Science at Home[5].

Besides these specific-context tools, there are general purpose web analytics data collection tools such as Google Analytics (GA)[6] and Piwik[7], the leading open-source alternative offering similar functionalities to GA (for a full list, see https://en.wikipedia.org/wiki/List_of_web_analytics_software). Using GA brings the additional benefit of being able to incorporate the demographic information that Google gathers on its users worldwide into analysis, which can be used to build the participant segment profiles. Open source analytics frameworks such as Piwik allows CCS projects to preserve ownership/ guarantee confidentiality of the analytics data if the self-hosting option is chosen.

To our knowledge there are no stable standalone learning analytics tools yet. A thorough state of the art research started in 2014 is available at

[4] https://unity3d.com/services/analytics
[5] http://scienceathome.org/
[6] http://www.google.com/analytics/
[7] http://piwik.org

http://edutechwiki.unige.ch/en/Portal:_Data_mining_and_learning_analytics_tools. At present, most of the developers of CCS projects rely on server logging and on collecting data via Google analytics.

Although the framework presented here is independent of the analytics data collection tool, the selection of the tool is an important decision that impacts the entire process of designing, deploying, implementing and collecting the analytics data. Among the criteria that influence the selection of the data collection tool, we mention: the availability of the tool (immediacy and sustainability), its implementation and testing time, its accessibility (to multiple users with access rights management capabilities), its treatment of the privacy issues, its accuracy (for instance, Google Analytics in some cases, reports only a sampling of the over-all data), the GUI and interactive capabilities of first-hand manipulation, and finally, the availability of demographic info of the users.

Figure 1 shows an example of the different components involved in the process of collecting and analyzing quantitative data sources (survey and analytics data) of two pilot projects, part of the European Citizen Cyberlab project. Analytics data are collected through the use of a client-side analytics event generator: the CCLTracker javascript library (Fernandez-Marquez, et al., 2016) and then stored with Google Analytics. Survey data are collected through a LimeSurvey platform directly launched from the citizen science platforms. Data from these two sources can be cross-referenced since users are given the same anonymous identifiers in both cases. Data are exported as CSV files and can be imported into statistical packages for analysis. In our case, we used SPSS for the analysis of survey plus analytics indicators data. R was used to filter analytics data, to compute indicators (metrics computed based on the raw analytics data) and to conduct the profiling analysis introduced in the example of application section of this paper.

2. A FRAMEWORK TO USE LEARNING ANALYTICS IN CITIZEN CYBERSCIENCE PROJECTS

2.1 Overview of analytics in citizen cyberscience

The analytics data that we can collect and analyse is rich and varied in scope; they allow creating explanatory models of learning. Some data give information about the demographic profiles of the participants such as age, interests, gender, and location. Other data reflect engagement with the project through time. A third group records interaction with various systems components, and indirectly tells us about their learning progress. Even the participant creativity and collaboration can be tracked with analytics.

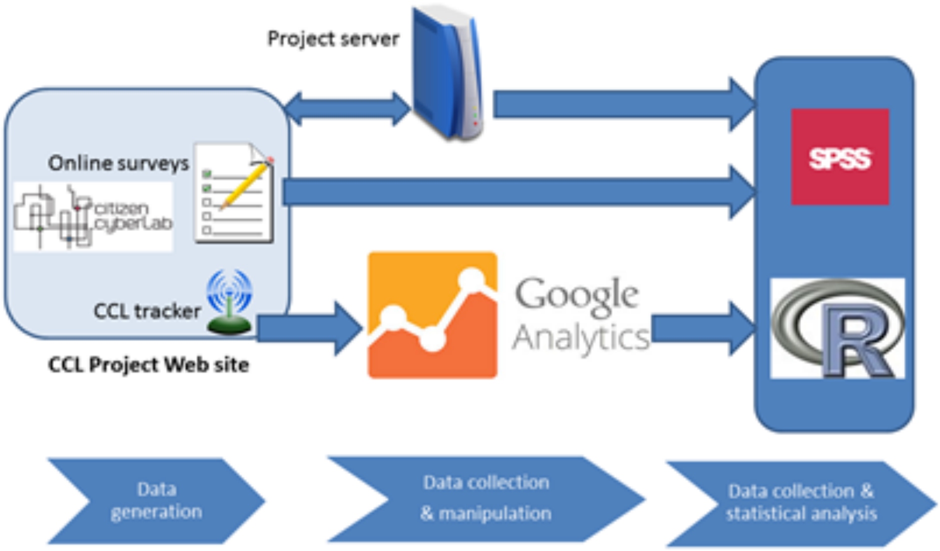

Figure 1 The analytics data collection scheme in the Citizen CyberLab pilot projects.

The proposed engagement-related analytics data inspire from the engagement conceptual model of O'Brien and Toms (O'Brien & Toms, 2008), though they are limited to infer on the engagement through time. In fact, analytics might not be naturally adapted to infer on other dimensions of engagement. Engagement through-time analytics data are based on the observation of activity and inactivity periods as well as on the activity intensity. Analytics data seem to be a very convenient data source for monitoring user activities which can be aggregated into multiple engagement indicators. Ponciano and Brasileiro (Ponciano & Brazileiro, 2014) applied this conceptual model to study engagement profiles in astronomy projects from Zooniverse. The engagement profiling they conducted was based on four indicators computed on a daily basis:

(1) The daily devoted work represented by the average activity duration through an active day,
(2) the activity ratio which is the ratio of the number of active days to the total period of activity,
(3) the relative activity duration which is the ratio of the total period of activity to the period of possible activity, i.e. the period from the first activity till the end of the project, and finally
(4) the variation in activity represented by the standard deviation of the idle time between active days.

Our framework extends these engagement metrics with others, namely, **duration of participation** which is the span of time during which a participant returns to the project, the **number of active days** during the duration of participation, **peak daily devoted work**, **total devoted work** during the entire period of activity, and the **skewness of the daily work** through the period of activity. The skewness might reveal the pattern of engagement through time: whether the participant starts enthusiastically and then loses interest, or, on the contrary, whether, (s)he starts slowly and gets more engaged as (s)he participates further.

Learning-specific analytics reflect performed actions that are potentially related to learning outcomes (e.g. time to complete a task, number of tasks done by the users, completion or abandonment of a tutorial, or the score attained in a specific activity, etc.). For instance, we use task completion time to infer on the needed effort to complete a specific task. Its evolution through time can inform about the learning curve of the participants. In the same terms, we can analyse the time series of scores related to a given repeated task. Also, correlations with completed tutorials can also inform about the impact of offered tutorials on learning.

Most importantly, our framework suggests that learning analytics data should be derived from well-defined expected learning outcomes of the CCS project. Also, they can be designed to reflect different learning dimensions from those presented in section 1.1 that are adapted to be inferred by analytics, e.g. the project mechanics, pattern recognition skills, and on-topic learning.

With the proposed learning analytics data, we can go beyond the computation of simple indicators as those proposed in Table 1 and suggest more complex analysis. The CCS project designers can identify specific activity paths, and study the impact of these paths on participant learning. For instance, VAS game appeared to be a complex game. Its designers identified an expected path (a sequence of actions) that a good player is supposed to complete sequentially, well-designed analytics data with proper time stamping allow to detect these paths in the activity of each participant and then to infer on their impact on the individual learning experience.

Creativity and collaboration are also two important aspects that citizen science projects would tend to stimulate. Analytics in the large sense can also be used to detect and evaluate creativity in the interaction of participants; Jennett & al., for instance, indicate that an active project community is a good stimulator of creativity (Jennett, Eveleigh, K., & Cox, 2013). Data such as the discussion boards of project forums are also potentially useful for assessing learning and creativity through methods of text analysis such as topic modelling, named entity recognition, key phrase extraction, or sentiment analysis.[8] It could also be interesting to conduct a social network analysis and explore how the participants interact through the project communication channels.

[8] see http://edutechwiki.unige.ch/en/Portal:_Data_mining_and_learning_analytics_tools or http://www.tapor.ca/ to explore existing tools.

The matrix in Table 1 provides some generic analytics that citizen science researchers may be interested in collecting, and then combining and summarizing into meaningful indicators. Data and indicators in the matrix are classified into five categories: **demographic, learning, engagement, creativity and collaboration.** The second column contains analytics data that can be combined into indicators as those cited in the third column. These indicators can be later used in the analysis of many aspects and interactions of any of the aforementioned categories. Obviously, the matrix is not exhaustive, and not all of the suggested analytics are relevant to all types of projects (for instance, due to their pilot nature, the projects we studied lacked meaningful collaborative and creativity analytics data).

A thorough examination of the proposed indicators reveal that they can further be separated into explanatory indicators and (dependent) measuring indicators. For instance, regarding the learning analytics, the number of completed tutorials is a variable that contributes to the explanation of how learning is occurring, while the duration that a participant needs to reach a specific level or, or the score (s)he achieves can be considered as measures of learning. For simplicity sake we don't consider this distinction here as it also depends on the statistical analysis to be applied to the analytics data.

Table 1. Overview of analytics data of interest in Citizen Science.

Category	Analytics data	Possible indicators (per participant)
Demographic	Age	
	Gender	
	Location / language,	
	Occupation	
	Referral[9]	

[9] Referral is the originating site from where visitors arrive to the CS site. Referral traffic information might help in identifying external sources that are most valuable in referring to the project site.

Category	Analytics data	Possible indicators (per participant)
Engagement	Date of first activity Date of last activity	Activity duration relative activity duration (if the project has a deadline)
	Active days dates	Activity ratio Variation in activity
	Nb. completed/interrupted tasks per activity day	Average Nb. of tasks per active day Total Nb. of tasks over the activity duration Peak Nb. of tasks per active day Skewness of activity
	Session/daily duration of activity	Average session/daily duration of activity Peak session/daily activity duration Skewness of session/daily activity
Learning	knowledge pretest and posttest(s) answers	Classification of the participant (with/without prior knowledge, expert, etc.)
	Accessed tutorials	Nb. of accessed tutorials
	Percentage of completion of each tutorial	Average percentage of completion of tutorials Nb. of completed/skipped tutorials
	Time spent on each task (completed or interrupted)	Average time spent on (completed/interrupted) tasks globally or daily
	Level achieved and date	Classification of the participant

Category	Analytics data	Possible indicators (per participant)
Learning (continued)	Individual scores or any other value computed or achieved by the participant	Daily or global average score
	Percentage of completion of each task	Average percentage of completion globally or daily
	Nb. completed/interrupted tasks per activity day	Percentage of completed tasks, globally or daily
Creativity	Nb. artifacts produced	
	Nb. of blog posts	
	Length of blog posts	Average length of blog posts
	Nb. wiki contributions	
	Length of wiki contributions	Average length of wiki contributions
Collaboration	N artifacts shared (“words”, pics, etc.).	
	Nb. forum messages	
	Nb. of blog comments	
	Nb. chat messages on public channels	
	Word count of forum/chat texts	Average word counts

2.2 The framework

In the following we use the term platform to describe any type of citizen cyberscience environment that provides a common working area for participants: these can be projects, games, platforms, or social networks, etc. We consider here analytics data in the narrow meaning, i.e. low-level data that track the interactions of a participant with the web interface of a CCS project. And we will mainly focus on learning and engagement.

Analytics data definition

The first step in setting up learning analytics in a CCS project is the definition of the analytics data, i.e. what we are going to measure and how we are going to measure it. As analytics are the low-level data, their definition must directly stem from the learning outcomes that are initially expected from participating in the project. Project designers, educators and developers must first reach an agreement on the learning outcomes to be evaluated. These outcomes should be SMART (specific, measurable, action-oriented, relevant, and time-related (Piskurich, 2011)). A good starting point for the definition of citizen science learning outcomes would be the User's Guide published by the Cornell Lab of Ornithology in 2014 (Phillips, Ferguson, Minarchek, & Bonney, 2014).

Once they have agreed on learning outcomes, the team must agree on the corresponding indicators to assess each outcome, and finally on the low-level analytics data (also called analytics events) necessary to compute the indicators. Obviously, the definition of analytics can go through an iterative process but developers should be aware that the implementation of analytics should start early in the phase of development and should be tested during the test and pilot phases since introducing analytics incrementally after project start will limit the period during which meaningful analytics data can be collected for an acceptable number of participants.

As an example of a common indicator for many CCS projects, bad clicks around the project interface are an indicator of how well participants master the interface. An analytics event can be generated each time a participant clicks in a wrong place. The event can include information about the part of the interface where the bad click occurs, and on the time of occurrence. Later, several indicators can be computed, depending on the level of detail needed. For instance, a global ratio of bad clicks can be computed and analyzed. Observing the evolution of this ratio through time might reveal if the users are improving and learning how to use the interface appropriately. It is also possible to make inferences about the usability of different parts of the interface by using the details in the events that inform about the placement of the bad click.

More complex learning outcomes might involve many different analytics events or require tracking the chronological sequence of events. For instance, following an adequate playing strategy in a CCS game can be considered as an expected learning outcome. This playing strategy can be detected if a set of actions is executed in a specific order. In this case, the needed analytics data might involve several user actions and their sequencing.

Analytics data generation and collection

Once the analytics data are defined, they need to be implemented through client-side analytics libraries, either domain-specific ones such as RedMetrics or Unity (mentioned above) or by using generic analytics packages such as the CCLTracker JS library that is specifically designed to generate general learning analytics (Fernandez-Marquez, et al., 2016). One highly desirable feature of CCLTracker is its high-level API to ease the implementation of complex client-side monitoring tasks, such as time watching a video, or time spent doing a task, etc. As with any piece of code, analytics implementation should be carefully tested to be sure that we are gathering all the needed events and related data.

Subsequently to testing, the data collection can start. It involves observing and recording the interaction of participants with the citizen science platform. Data are generally logged and stored for later processing, yet real-time tracking might also be available (for instance if GA or Piwik are used)

Analytics data processing

Typically analytics data are collected according to the following format:

User Id	*Combined event*	*Complementary info*	*Date*	*Time*

Figure 2 A suggested format of an analytics data structure

User Id is an anonymous identifier that the developers define and make sure it is shared among all the data sources of the activity of the participants, i.e. analytics, online surveys, in-app questionnaires, etc.

Combined event is an event tag combined with some extra information. The extra information can, for instance, indicate the part of the UI where it occurs, or on the answer of the participant in a related activity.

Complementary event info is a field that does not always contain relevant information. It might be used for some types of events to give a timestamp, a percentage of completion of an activity, or the duration of time spent on the activity.

Date and **time** are the timing information to be provided for each occurring event. In some cases, a more precise timestamp is needed in order to chronologically order the events, and in this case it can be transmitted in the complementary info field.

Typically, on a normal active day, participant activities can generate thousands of events. These events are collected and processed and then aggregated into the defined indicators reflecting the learning outcomes.

Analytics data analysis

Once the indicators are computed for each participant and stored in a dataset of the format below (Figure 3. Analytics dataset format), the statistical analysis of the indicators can start and it is at this stage that it is possible to combine or merge the analytics data with other data sources based on the user Id's.

User Id	*Indicator1*	*Indicator2*	...	*IndicatorN*

Figure 3. Analytics dataset format

The exploration, visualization and statistical analysis of the resulting data will help with testing research hypotheses and answering specific questions, for instance, regarding the effect of engagement in citizen science projects on some aspects of the participant learning experience.

At this stage, it is potentially needed to go through an indicator/feature selection process. As analytics data collection tools allow for the generation of rich datasets, Parts of the data might be either redundant or irrelevant to the analysis of a specific aspect of engagement and learning. In order to better adjust the analytics dataset to the needs, we can rely on feature selection methods that are adapted to the statistical analysis we are interested in.

Finally, if we want to compare different CCS platforms serving the same purpose or same domain, we might design complex indices or KPIs (key performance indicators), and analyse the performance of different platforms against these KPIs.

3. EXAMPLE OF APPLICATION

The framework proposed here is applied to the two pilot projects mentioned in the introduction: GeoTag-X and Virtual Atom Smasher. Ideally, analytics should be gathered for long periods and with thousands of participants to lead to interesting analysis. We were only able to track our pilot projects for short periods of time and participants were only few hundreds; in spite of this, a typological analysis returned interesting results regarding short-term engagement-learning profiles.

We start by introducing the profiling approach that we followed and then for brevity's sake, we present the analysis results of one pilot project: GeoTag-X. A similar approach was followed and results were also obtained for VAS and are briefly presented in (Fernandez-Marquez, et al., 2016). A full analysis is available in the Citizen Cyberlab deliverable (Kloetzer L. , Schneider, da Costa, Abu-Amsha, & Jennett, 2015)

3.1 Profiling participants based on their analytics data

Once the different indicators of interest have been set, many statistical analysis methods can be used to gain insight into the different aspects of the participant behavior. Departing from the hypothesis that there is a correlation between the engagement through time and the learning outcomes, we propose a strategy to cluster participants based on their engagement and learning indicators. We drew inspiration from (Ponciano & Brazileiro, 2014) where the authors focused on engagement profiles while we use both engagement and learning indicators.

We conducted an exploratory cluster analysis on analytics datasets with the objective of identifying participant types. Ponciano and Brazilero applied clustering analysis on a set of engagement indicators of participants in two projects from the Zooniverse family, tracking tens of thousands of participants over more than 18 months. Our datasets extend to a few months with only a few hundred participants. We were curious to see if applying the same approach as in (Ponciano & Brazileiro, 2014) on such limited datasets would reveal any interesting patterns.

Our preliminary analysis of Virtual Atom Smasher data revealed that, for such small datasets, clustering with both types of indicators give more interesting results than with the unique engagement indicators. In fact, clustering represents a first-hand analysis and allows for the identification of participants exhibiting similar behavior patterns regarding learning and engagement.

Regarding the profiling methodology, a classical hierarchical clustering can be applied to a dataset where rows represent the identified participants in a CCS project, and columns represent the respective scaled values of indicators deduced from the analytics of each participant (as depicted in Figure 3. Analytics dataset format. Scaling the values is required to ensure the good performance and interpretation of the clustering output as the selected indicators might have very different value ranges

Clustering is used here to identify groups of users who share similar engagement and learning characteristics. The number of clusters is not known in advance, many advanced techniques are available to estimate it. A first-hand approach would be to observe the tree diagram of the hierarchical clustering (also known as dendrogram) and see how many clusters seem clearly separate. Once the number of clusters is decided, we would examine the centers of the clusters, which are the means of each indicator inside each cluster. These centers help to assess how distinct the clusters are and what are the main characteristics of each cluster. Many metrics are also available to assess the quality of the clustering analysis. Their presentation falls beyond the scope of this paper.

Correlation analysis is also available for testing hypotheses regarding, for instance, the relationship between different types of engagement and learning of specific aspects of the project. Predictive models can then be developed to predict which type of engagement could lead to the learning outcomes that most interest the CCS project leaders. Again, such analysis requires datasets of reasonably big sizes to be significant and lead to interesting results.

Experimentations with Virtual Atom Smasher and GeoTag-X analytics were done in R and the results for GeoTag-X are presented next.

3.2 Profiling GeoTag-X participants

As mentioned in the introduction, GeoTag-X is a crowdsourcing platform where the main tasks are: identifying relevant photos to a specific disaster, conducting detailed analysis of those photos and potentially geo-referencing them as precisely as possible.

A typical task in GeoTag-X concerns answering a few multiple-choice questions about a displayed photo related to a specific disaster context. The platform provides training tutorials that are supposed to be completed prior to every different theme (called projects in Geotag-X) but the tutorials are not compulsory and can be skipped. The participants can analyse the same photos several times as long as the photos are available for analysis (A photo is hidden once a fixed number of analysis is achieved)

We tracked the activity of the users of GeoTag-X from the 5th of August 2015 to 21st of October 2015. During that period we gathered learning analytics from 959 users, 706 participants were anonymous and 252 participants were identified. The participants completed a total of 6837 tasks. 6669 tasks were done by identified users and only 168 (8.5%) by anonymous users. In fact, despite the high number of anonymous participants, the completed tasks were mainly done by logged-in participants

As a first hands-on exploration of what information can be inferred using the collected analytics, a hierarchical clustering is implemented in order to discover the profile of the users without using any other prior information. Table 2 classifies the different indicators used in the profiling analysis in two types: learning indicators and engagement indicators. Each indicator is computed for each individually identified participant based on her/his collected analytics data. The events mentioned here are the analytics events explained in section 2.2 and that reflect on the activity of a given participant.

It is to be noted that the short data collection period didn't allow for the computation of other interesting indicators, for instance we could not collect enough data to compute indicators around the variation in activity through time, instead we only computed the duration of participation during the data collection period as the number of days separating the last day of activity from the first day, then, we computed the number of active days during this period.

ENGAGEMENT INDICATORS	LEARNING INDICATORS
• Total duration (in days) • Nb. of active days in the whole duration • Mean nb. of events per day • Total nb. of events in the total duration • Peak nb. of events per day • Skewness of nb of events	• Mean nb. of bad clicks per day (independently of the location of the bad click) • Ratio of bad clicks (bcr) • Total nb. of started tutorials • Total nb. of completed tutorials • Total nb. of skipped tutorials • Mean time before skipping tutorials • Mean time to complete tutorials • Total nb. of distinct completed tasks (info provided from server-side) • Total nb. of started tasks • Total nb. of completed tasks (not necessarily distinct) • Mean-min-max-standard deviation of task duration

Table 2. Indicators used in a cluster analysis of participants in GeoTag-X.

The hierarchical clustering mainly revealed four different participant profiles in GeoTag-X:

Users who did not submit any task (no tasks)
When the dataset was explored, we observed that 77 did not submit any tasks during the studied period. These participants visited the web site and had a limited activity with a seemingly higher bad click ratio than the other groups. These participants are grouped in one group and excluded from the clustering analysis because they lack the indicators related to task activity.

Explorer
Users with a low level of engagement, who contributed on average less than 3 tasks per user. We identified 55 users in this group. Only 10 of them came back for a third time.

Ephemeral
The group of participants who return slightly more often within a short period of time (typically within less than a week), but who, in contrast to the explorer group, has meaningful activity in the area of task submission (twenty

tasks per user on average). We identified 89 users in this group.

Committed The group of users who return several times and submit a lot of tasks (one hundred tasks per user on average).

Table 3 below presents the centers of the different groups to which GeoTag-X participants belong. Some interesting indicators of the cluster centers are also depicted in Figure 5.

Table 3. The mean values of the indicators of GeoTag-X activity according to the different participant groups.

	No Tasks	**Explorer**	**Ephemeral**	**Committed**
Sizes	**77**	**55**	**89**	**31**
nb. of active days in the total duration	1.75	1.85	2.06	9.16
total duration (in days)	6.92	5.27	3.25	32.52
activity ratio (nbActivDays/duration)	0.80	0.75	0.85	0.39
mean nb. of events per day	19.43	47.36	133.07	133.13
total nb. of events in the total duration	32.77	80.49	242.78	1060.32
peak nb. of events per day	27.25	61.60	177.72	368.32
skewness of nb. of events	0.34	0.07	0.07	0.78

	No Tasks	**Explorer**	**Ephemeral**	**Committed**
mean nb. of bad clicks per day (independently of the location of the bad click)	2.27	4.69	8.65	5.77
ratio of bad clicks (BCR)	0.13	0.10	0.06	0.05
nb. of started tutorials	0.81	1.62	2.42	7.29

nb. of completed tutorials	0.21	0.69	0.76	1.48
nb. of skipped tutorials	0.22	0.38	0.90	3.58
Mean time before skipping a tutorial*	122.88	137.99	121.96	52.80
Mean time to complete a tutorial*	449.82	203.82	283.26	243.74
total nb. of distinct completed tasks**	7.40	11.11	30.87	163.52
total nb. of started tasks	3.13	6.76	29.48	142.00
total nb. of completed tasks (not necessarily distinct)	0.00	2.51	19.20	99.23

	No Tasks	**Explorer**	**Ephemeral**	**Committed**
total nb. of distinct started tasks during the analytics collection period	2.60	5.78	26.15	118.52
total nb. of distinct projects in which tasks are at least started	1.10	1.24	1.57	2.97
mean task duration*	NA	83.73	79.25	63.61
max task duration*	NA	100.17	170.75	185.66
min task duration*	NA	68.09	19.56	5.73
standard deviation of task duration*	NA	29.85	51.56	46.54

* *Durations are provided in seconds*
** *Information provided from GeoTag-X server and not from the analytics.*

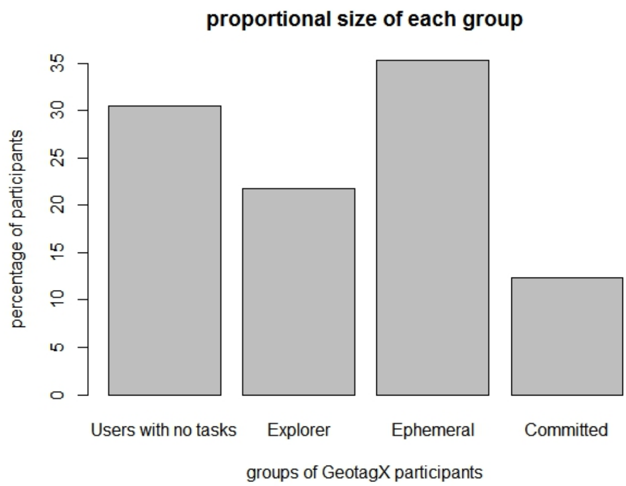

Figure 4. Distribution of GeoTag-X participant types in terms of number of participants

The group distribution resulting from the typological analysis shown in the head of Table 2 and depicted in Figure 4 indicates that 47.6% of the identified participants in GeoTag-X (the ephemeral and committed groups) had a meaningful contribution. Individual participants from these two groups typically submitted more than twenty different tasks and contributed to several projects (or themes) on the site (Figure 5 (c) and (e)).

Figure 5 (a) depicts the longer durations (in days) during which **committed** participants stayed connected to the project (i.e. returned to it) in contrast with the other groups. The number of active days of this group is also higher. We observe that the higher level of participation (number of tasks submitted) involves a higher number of visits (more active days) and longer durations during which participants stay on the website and return to the project.

Event statistics in Figure 5 (b) show the higher intensity of activity of the committed group, and also reveal that the ephemeral group has a higher activity than the explorer group.

The total task bar in Figure 5 (c) uses the data stored on GeoTag-X server and shows the total number of tasks that each participant contributes independently of time. That is why we see a small number of tasks attributed to the first group who submitted no tasks during the period of the analytics collection. This indicates that participants from this specific group had a limited activity before the analyzed period. Their activity type is closest to the explorer group.

Figure 5 (d) reveals a disparity between the minimum times to complete a task for each group. One might expect that the longer the participants remain on the GeoTag-X website, the faster they manage to submit tasks. As detailed in

Table 4, the global correlation confirms this hypothesis with a significant negative correlation although of a small value. The in-group correlations are not significant since the number of active days is small for the participants in the explorer and ephemeral groups, and the number of participants is not large enough in the committed group.

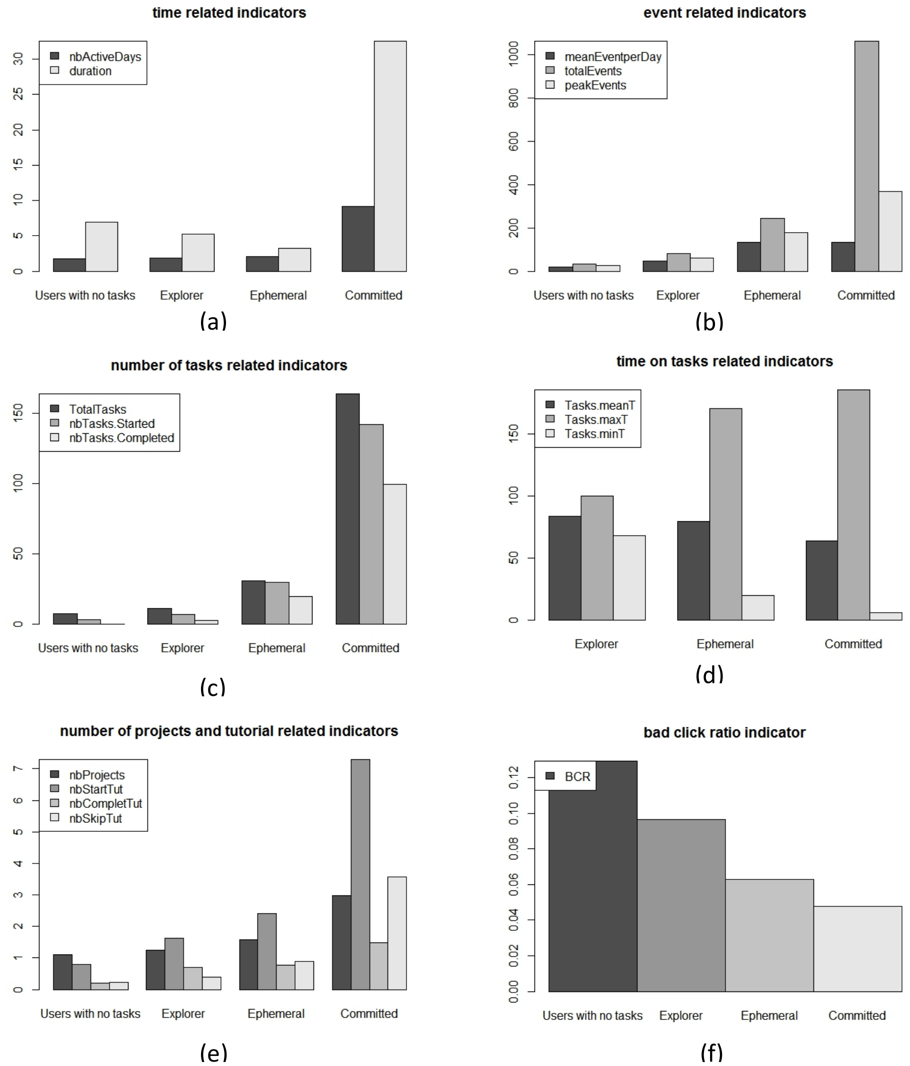

Figure 5. Some indicators of GeoTag-X activity according to the different participant groups.

		Minimum task duration X Nb. Active Days
Explorer	**Correlation**	0.138
	significance	*0.3*
Ephemeral	**Correlation**	-0.061
	significance	*0.6*
Committed	**Correlation**	-0.138
	significance	*0.5*
Global	**Correlation**	-0.218
	significance	*0.004*

Table 4. Correlations between the minimum time to submit a task and the number of active days, in each group and globally for all the participants.

As the duration to complete a task is an indirect measure of how confident the participant is regarding the photo analysis (s)he is conducting, it is interesting to explore whether these durations differ significantly among detected groups. A one-way ANOVA is also applied to test if the value of the minimum duration to complete a task differs significantly among the three groups. The test confirms this difference with a high significance (p-value < 0.001). The same ANOVA analysis is also applied to the mean duration and also confirms differences in values among groups but with a weaker significance (p-value= 0.02921). In fact, the difference in mean durations to complete a task among the ephemeral and the explorer groups is not significant as confirmed by a t-test. To properly infer on learning, and with richer analytics data, it will be interesting to study the time evolution of task completion duration to see if the participants become more expert and achieve the tasks faster with time.

It is, in principle, possible to merge analytics data designed according to the proposed framework with online survey data of the CCS project. Interesting analysis can be conducted if enough participants are tracked with analytics and also fill in the surveys. GeoTag-X proposed two online surveys (Kloetzer L. , Schneider, da Costa, Abu-Amsha, & Jennett, D6.3 Learning in Citizen Cyberlab, 2015)— a pre-test offered at the sign-up and a post-test offered after a user has completed 30 tasks. Both short surveys were designed in cooperation with the pilot project team to measure project specific learning and reasons motivating participants to participate in GeoTag-X. A short analysis that combines analytics and surveys data is presented in the project deliverable (Kloetzer L. , Schneider, da Costa, Abu-Amsha, & Jennett, 2015).

We see here that the typological analysis of short-term engagement and learning indicators revealed different patterns from the ones revealed in long-term engagement profiling presented in (Ponciano & Brazileiro, 2014) which is expected as we included learning indicators and we only analysed short-term activity. Interestingly, there were similarities between the analysis results of Geotag-X and VAS analytics data with slightly different profiles of VAS players. The typological analysis separated VAS participants into those who visited the game only for one day and never returned, those who explored the game for short periods, and those who were committed. A distinct group is detected among VAS players, and includes players who seemingly were very active but apparently didn't manage to play properly and then abandoned the game after few days. It will be interesting to apply the same learning-engagement typology analysis to different types of CCS projects and see if common patterns arise. Also, we are aware that applying the same analysis to larger datasets might change the resulting typology and this should makes part of our future research plans.

4. GOOD PRACTICES IN THE USE OF LEARNING ANALYTICS

Our experimentation with the learning analytics of both VAS and GeoTag-X reveals that valuable insights could be gained from analytics data. The full exploration of all avenues requires long periods of data collection and more participants. The following list sketches general recommendations for a full exploitation of learning analytics. They are the result of our experience with the learning analytics of the two pilot projects VAS and GeoTag-X, using CCLTracker (Fernandez-Marquez 2016) and GA services for the collection of data. Data manipulation and analysis are done in R.

Design Aspects

- Analytics should be present starting from the first phases of the design of the projects.
- The design of the tracking activity is a collaborative work between educators, designers and developers to define the relevant expected learning outcomes and how to track them.
- The definition of analytics is a top-down process: After specifying the Expected Learning Outcomes according to the different dimensions of the learning, the needed indicators should be derived followed by the needed analytics to compute these indicators. A bottom-up feedback is also necessary, as we need to be sure that the analytics we expect to build our indicators are practically available.
- We have to keep in mind that analytics cannot track everything. For instance, the duration of a session is a very questionable concept as a user might keep the page/task active while not working on it and it is difficult to guess when (s)he really abandons.

- Analytics data can be combined with electronic surveys and questionnaires. They can also be combined or triangulated with server-side logs to better track the behavior of the users.
- Based on the expected participation in the CS project, the data scientist should forecast and allow for reasonable activity duration before starting the analysis.

Technical Aspects

- It is important to start by setting up reliable and scalable user identification schemes respecting the privacy and allowing the connection with potential electronic surveys and questionnaires that users might also fill in.
- Anonymous contributions are important to many CCS projects; however, in these cases, we cannot carry out an engagement or learning assessment as anonymous users cannot be tracked through time even if they return several times to the project. In such cases, only contributions through individual activity sessions can be tracked without any identification of the users.
- In order to separate the event tracking logic from the specific service that collects the analytics, user behavior must be tracked locally (client-side) and interesting events are defined with a suitable data structure using, for example, a framework such as CCLTracker, then the data can be sent to GA, or any other analytics service or stored on the project servers.
- In general, we must explicitly track the start-time and the finish-time of each meaningful user action. Including the duration of the action allows also for simplifying the data processing. otherwise, each action should have a unique Id to detect the events that track its beginning and its end or its interruption. This ultimately makes the structure of an analytics event complex, and potentially dependent on the selected analytics collection and storage option (e.g. locally, GA, etc.), hence the events should be carefully designed from the beginning.
- Special attention should be given during migration of data, server logs and analytics schemes to a new version of the project platform, hosting environment, or web interface. Without backward compatibility of the data and the analytics, the use of analytics in the long-term will be compromised.
- Spare enough time to test analytics data collection and consider all the use cases. For instance, we noticed that when tracking clicks on hyperlinks, if the user decides to open the link in a separate tab to keep the project page open, the click event is not tracked.
- Statistical analysis could be done in any statistical packages such as SPSS or the programming language R.

Finally, we would recommend storing analytics data locally to keep the ownership, have full control on the data, and be confident of its quality. If the demographic data offered by Google is really important for the project team and it is not available through other channels, Google analytics service can be used to track global activity on the project platform without necessarily implementing a tracking system that sends all the events to GA, but in this case, one should be aware that the possibilities of crossing different types of analytics can become limited, also, that extra time should be devoted to develop the visualization and manipulation capabilities that Google analytics avail to its users through the GA web interface.

5. CONCLUSION AND FUTURE WORK

Most citizen science projects have educational goals and expect to improve the scientific literacy and the public understanding of science in addition to their ultimate goal of supporting researchers in accomplishing tasks with the help of the crowd. Learning analytics is a source of valuable data for tracking participant activity and understanding how and what they are learning when contributing to online citizen science projects.

Also, analytics can be most helpful in feedback loops as it allows for a better understanding of participant profiles and behavior in CCS projects. It also helps programs to develop adapted actions in four different directions identified in (Bonney, Phillips, Ballard, & Enck, 2015), namely project design, goals achievement (outcomes) measurement, diversification of targeted volunteers through adapted outreach actions, and ultimately, the exploitation of analytics in conjunction with other evaluation tools might reveal new research directions to explore.

When the analytics data are well-defined, they offer many possibilities to fine-tune the analysis of the participant behavior. With further experimentation, our framework can be extended to propose such possibilities. For instance, Jordan & al. (Jordan, Ballard, & Phillips, 2012) suggest that some projects with long time run and long-term participants may consider different types of learning outcomes for different levels of participant engagement. In other words, it may be worth engaging long-term volunteers in different types of activities with different learning outcomes. While, short-term volunteers who might participate only a few times, may require less training, and still provide meaningful contribution and potentially also meaningful learning of different aspects.

Also, depending on how analytics data timing is defined, a detailed analysis of the activity of the participants can be conducted to potentially detect chronological patterns. For instance, previous studies revealed some weekend bias in the CS data collected to support phenology studies (Cooper, 2014). Such analysis might in turn inform outreach actions: If we know that citizen scientists are more active on weekends or during specific periods, tailored actions can be launched at convenient points in time to encourage them to connect to CCS projects.

Although our experimentation with the learning analytics of two pilot CCS projects has many limitations, it allowed us to gain insights into how analytics data should be designed to help assess the learning of the participants. The framework that we propose in this article may help other CCS project teams to methodically include learning analytics in the project development cycle in order to avoid the pitfalls that we identified during our own research and practice. Our future research will make use of this framework to analyse richer analytics datasets and explore which types of analysis are the most adapted to infer on CCS participant learning experience from the low-level analytics data.

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