Abstract

Next generation innovations and increasingly higher expectations for business value and security are rapidly shaping the Information Technology (IT) industry and workforce of today. Against this backdrop, a datathon can address the skill gaps and various constraints of traditional modes of summative assessments which include projects and assignments for computer science students. A datathon is a portmanteau, coined from the words “data” and “marathon”. It is a variant of a hackathon with the focus shifted towards participants from the data science community working with data and predictive models to complete a given challenge. At the School of Informatics & IT, the module Statistics and Analytics (SANA), which is offered to Year 1 students, incorporates learning both statistics and data science skills. This module’s learning objectives include data-driven activities, such as filtering through datasets with multiple variables, handling non-traditional data types, learning essential statistical models, categorizing raw data and collaborative team work. We hoped to elevate students’ achievements to higher levels than traditional projects through an authentic and performance-based datathon. This paper highlights the design, structure and eventual actualization of the assessment metrics of the datathon. It describes how the lecturers prototyped a hybrid model of a datathon to meet the principles of assessment criteria. We also elaborate on how the datathon can gauge students’ underlying skills and the quality of the assessment outcomes. Finally, this paper will indicate the results of the study and propose recommendations for future datathons.

Keywords: Digital innovative learning, datathon model, collaborative learning, learning analytics, data-driven

Introduction

Generally, Warner, J. & Guo. P. J. (2017) has characterized datathon as a data focused computer programming event or a pitching competition to display cases of programmed prototype digital innovations driven by analytical insights. Datathon is a variant of a hackathon with its focus shifted towards data. The purpose of a datathon (Anslow, C, 2016) is for data science community’s participants to practice data science and analytics skills for either work or studies. Organizations have began to provide data to encourage external stakeholders to participate by improving existing services (Hjalmarsson & Rudmark, 2012). In Calgary, datasets are provided by non-profitable organizations for ‘Data for Good’ event in exchange for data-driven insights resulting from the datathon. (S. Seyffarth, 2015). Similarly, in Sweden, Innovation for Sustainable Everyday Travel (ISET), (Hjalmarsson, A., and Lind, M., 2011) provides open data for innovation to enhance sustainable everyday travel.

Briscoe, G. & C. Mulligan (2014) have traced the origins of hackathon back to 1999 when open-source software developers OpenBSD and Sun Microsystems introduced hackathons for developers to create software on their respective platforms. In contrast to the earlier hackathons, hackathons are now prevalent activities for software companies, like Google and Facebook (Alexandra Chang, 2012). This rising popularity is due to the alignment of company culture with hackathons’ rapid-fire prototyping, fusion of expertise, experience, skills and innovation. The hackathon phenomenon is known for its innovativeness and creativity on how a problem is solved (S. Zheng, 2013) at events. The proliferation of hackathons, over 400 hackathons are reported from 2000 to 2012 worldwide (S. Leckert, 2012) across several disciplines forms the culture of digital innovation. Being more collaborative than competitive, the present events contain a spectrum of activities, enabling students to pilot new ideas, synergizing technopreneurs and innovators in context on emerging trends, and serving as de facto hiring arena for tech companies.

Briscoe, G. & C. Mulligan. (2014) explained that hackathons have spiraled into different alternatives. With the burgeoning amounts of data and a growing data science community, datathons assemble data enthusiasts to model data-driven solutions. Typically, datathons are known to be intensive and accelerated competitions which are coordinated in a business environment. It is recommended to assemble datathon participants in interdisciplinary teams (Aboab et al., 2016), although...
monodisciplinary teams are fine. So-called datathons transfer the hackathon concept to challenges with regards to data analytics (Aboab et al., 2016). Applying analytics requires a combination of capabilities: analytics, statistical, mathematical, and programming skills (T. H. Davenport & Patil, 2012). The range of tasks can be varied, from data preprocessing and cleansing to data mining and data visualization (Anslow, Brosz, Maurer, & Boyes, 2016).

The purpose of this study is to explore how the synergies and innovations in a hybrid model of datathon can fit into the complex educational system as an alternative, authentic and summative assessment. What are the modifications needed and constraints encountered to introduce it into the intricate educational system to measure learning? Concurrently, we will investigate corresponding assessment metrics and their mapping.

The research questions of this paper are: (1) What are the design parameters for a summative assessment using a hybrid datathon model? (2) How can we design effective assessment criteria and rubrics? (3) What are the perspectives of the participants?

**Implementation and structure of the hybrid datathon**

In the School of Informatics & IT, we propose and implement a hybrid model of datathon in place of a summative assessment. The primary reason is to evaluate students in environment similar to the IT workplace. In the educational context, (Wiggins, G., & McTighe, J., 1998) define summative assessment as a formal measurement of determining if students have sufficiently understood learning goals after a designated time period. Fulfilling such criteria is critical in tests, examinations and final projects.

In a datathon, identifying the right problem usually leads to success because a quick, tangible hack can be demonstrated at the end. Contrary to a datathon, it is imperative for us to concentrate on the design process (Artiles, J. A., & Wallace, D. R., 2013). In the educational context, we are expected to establish the problem, execute brainstorming, prototyping, end user feedback and evaluation. Thus, the design of an educational datathon has to incorporate all these parameters.

In the initial phrases of planning, two Year 1 logic and analytics cluster modules: Logic & Mathematics and Statistics & Analytics which were taught over 17 weeks are chosen for the datathon. These are core modules and their learning objectives are analytics acquisition, algorithm thinking, data cleaning and dashboard creation skills.

The datathon was held in the last week (week 17) of the semester. A week before the datathon (week 16), smaller groups of 5 to 6 students are already formed for individual classes. On the actual event, 12 tutors are deployed to 21 participating classes. The tutor’s role is to check the attendance of group members, introduce the dataset, provide directives and a set of general guidelines before its commencement. Since it is a scaled down hybrid model, time given for the various groups to brainstorm, acquire data, investigate complex relations and code a dashboard is limited to 6 hours at the learning labs with unlimited access to the internet.

Once the datathon begins, groups work intensely within the time frame from 9am in the morning till 3pm, after which they must cease work and present the dashboard end product with analytical insights to the panel of 3 judges, who are making their rounds to the teams. In the brainstorming session, certain innovative and resourceful groups are seen engaging with online tools which are not taught in the modules for further exploration and processing of given datasets. Some groups tend to be distracted and may take a much longer time to settle in. Many groups quickly work towards their goals and strategize their approach (Figure 1). In a few groups, a visible leader is leading and delegating work to the group in their distributed tasks. Finally, at the end of the 6 hours, teams have to cease work, upload their source codes to a server and give a demonstration. The judges would walk around the venue to assess the insights analysis of the end product using a standardized marking rubric.

**Design parameters for hybrid model of datathon**

In this section, we shall discuss the principles when we design the hybrid model datathon for its suitability as a summative assessment in the educational context.

![Image](image_url)

**Figure 1.0:** (a) Teams brainstorming in a learning space  (b) Data analysis using external tools (c) A team exploring the dataset (d) End-product from a team

Firstly, it is essential to evaluate the curriculum of the analytics cluster modules to ensure relevance of knowledge learnt. Analytics or data science addresses the exploration of data sets with different quantitative methods motivated from statistical modelling (James et al., 2015). Cleveland (W. Cleveland, 2001) emphasizes that students should analyze data and it should be a major part required of undergraduate programs in data science. The analytics cluster modules seek to introduce basic data science or knowledge generation from data. The general learning outcome expects students to transform raw datasets and build a dashboard. (Table 1.0). It is fitting to translate a small-scale datathon into several assessment tasks which fulfill the specific learning goals (Boud, D., 1995). The key activities identified in data value chains include data generation, data acquisition, data processing, analytics and visualization. (Miller & Mork., 2013) (Curry, 2016). Since, a data challenge emphasizes on analytics skills such as organizing raw
data, using different data types, sorting through datasets with variables and dashboard creation of insights, it is appropriate to model a summative assessment after a data challenge. As we can see, some key development phases in a data life-cycle are linked to the specific learning outcomes too.

Table 1.0: General and specific learning outcomes.

<table>
<thead>
<tr>
<th>Topic 5</th>
<th>Dashboard Building</th>
</tr>
</thead>
<tbody>
<tr>
<td>General Learning Outcome</td>
<td>Specific Learning Outcomes</td>
</tr>
<tr>
<td>Students should be able to:</td>
<td>Students should be able to:</td>
</tr>
<tr>
<td>5. transform raw datasets and build a dashboard.</td>
<td>5.1 identify data quality problems in a data source; 5.2 apply data transformation techniques to clean data; 5.3 build a dashboard using a visualization tool.</td>
</tr>
</tbody>
</table>

Secondly, the datathon is both focus-centric and tech-centric where the end product will address specific learning outcomes in our educational context. Briscoe & Mulligan, (2014) distinguish between tech-centric and focus-centric. Our datathon is tech-centric datathon as it focuses on software application with a specific visualization software, Microsoft Power BI. We assess our students’ notions of competence with respect to learning and software skills on dashboard building using this application. The assessment is suitably refined to map the datathon’s problem statements to our specific learning outcomes. Being focus-centric, our students have to demonstrate the ability to prepare data, discover insights and charts. In fact, (Boud, D. 1995) deems good assessment as one which closely reflects desired learning outcomes and the process of assessment has a directly beneficial influence on the learning process. We decide to challenge students on a formative approach in our problem statement for deeper cognitive thinking.

For example, a summative approach with specific learning outcomes (Table 1.0) is very structural, such as giving students a dataset, asking for step-by-step computation of variance, mode and inter-quartiles, plotting of data charts and building the final dashboard. Alternatively, a formative approach requires students to explore the same dataset and significant variables. Relying on their cognitive abilities, students have to compute suitable statistics and data charts to discover significant causal variables and their relations within the dataset without pre-identified variables (Table 2.0).

The application of data science is diverse, with focus on areas such as information security (S. Kumar, 2014), healthcare informatics (G. Zheng, C. Zhang, L. Li, 2014) and software engineering (T. Menzies, E. Kocaguneli., F. Peters., B. Turhan, 2013). Additionally, data understanding and domain knowledge are key prerequisites in the analysis process (Waller & Fawcett, 2013). Thus we provided 5 datasets in different contexts consisting information of hospital discharge rates, workers’ salary and age, geographical transport connectivity, industrial employees’ demographics, credit loans with customers’ credit ratings to the participants.

Thirdly, it is an authentic assessment, with what Wiggins, G. (1989) described as “contextualized complex intellectual challenges, not fragmented and static bits or tasks”. Cleveland (W. Cleveland, 2001) highlights that the practicing data analyst faces two critical tasks (1) the building of a model for the data; (2) estimation and distribution of the model. Cleveland (W. Cleveland, 2001) comments that it is vital for data science subject to carry statistical thinking to subject matter in various disciplines. Our fundamental datathon will allow students to deliver tangible products, a report and dashboard where new data insights are discovered from the quantitative charts while building real data analytics practices.

Table 2.0: Problem statement for the datathon.

<table>
<thead>
<tr>
<th>Specific criteria tested</th>
<th>Specific Learning Outcomes</th>
</tr>
</thead>
<tbody>
<tr>
<td>Deliverables: A report not more than 1000 words</td>
<td>State what you want to investigate in this given dataset. E.g. “Over the years, can we see some trends in the discharge rate of some diseases?” Do not use this question for your project. 5.1 Identify data quality problems in a data source; 5.2 Apply data transformation techniques to clean data; 5.3 Build a dashboard using a visualization tool</td>
</tr>
<tr>
<td>Data preparation or data cleaning steps that you have taken. Take screenshots of the step by step procedure that you have done.</td>
<td>5.2 Apply data transformation techniques to clean data;</td>
</tr>
<tr>
<td>Different charts that you have created. Take screenshots and do explain your choice of charts.</td>
<td>5.3 Build a dashboard using a visualization tool;</td>
</tr>
<tr>
<td>The insights or new things that you have discovered while looking at your charts.</td>
<td>5.2 Apply data transformation techniques to clean data;</td>
</tr>
</tbody>
</table>

In higher education, concerns about learning outcomes oriented perspectives in a discipline have been open to critical scrutiny. Some questions we need to answer are: Can graduates perform in the current “analytics 3.0” environment (Davenport, 2013)? Are current assessments the best performance measurement for related methods of analytics such as text, web and network analytics? (H. Chen, Chiang, & Storey, 2012) As Boud comments that traditional mastery tests are inadequate as the questions are often contrived and the cues are artificial as standard right answers equate to adequacy in achievements. Hence, the preference for a datathon in our case (Boud, D., 1995).

Assessment rubrics and criteria for datathon model

All assessments require evaluation parameters and these can either be explicit or implicit. (Black and William, 1998). The rationale of assessment is to capture complicated learning outcomes, implement realistic tasks, and use good instructional tools to include elements of collaboration and interaction among students. Earlier, we have devised the problem statement and students’ deliverables as criteria to match specific learning outcomes. Sadler (1998) commented that assessment begins with identifying a number of relevant criteria, then we measure the amount present on each criterion and we
combine the various levels or estimates into an overall measure of merit by means of a formula (Sadler, 1998). In an educational context of assessment, Scriven points out that it is usually necessary to justify (a) the data-gathering instruments or criteria, (b) the weightings and (c) the selection of goals (Scriven, 1967).

In the design of the datathon, there are 2 deliverables, a report and a dashboard. We map the specific criteria of the deliverables to the specific learning outcomes in our modules. (Table 2.0). In the report deliverable, all the specific learning outcomes are translated into essential criteria for measurement of learning competency of data analytics.

To provide clarity in the data challenge’s grading process, we propose a rubric with evaluative criteria. In this paper, assessment rubrics broadly refer to detailed grading with numbers or formulae and they are suggestive of broad quality levels (Sadler, 2009a). The creation of rubrics is in the teachers’ domain and we adopt Bigg’s structure of observed learning outcomes (SOLO, Biggs and Tangs 2007) where there is a transparent alignment between objectives, learning activities and assessment tasks. Likewise, each grade description has embedded within it a number of criteria and descriptors of our learning objectives. The rubrics for the panel of assessors are provided below (Table 3.0).

As an overview, we will discuss the design elements present in the datathon rubrics: specificity, scoring strategy, evaluative criteria and process. The rubrics enable assessors to grade tasks meaningfully and consistently. We have built evaluative criteria into the rubric to break down the grading into several smaller criteria.

Table 3.0: Marking rubrics for end-product dashboard

<table>
<thead>
<tr>
<th>Criteria</th>
<th>Excellent</th>
<th>Good</th>
<th>Average</th>
<th>Poor</th>
</tr>
</thead>
<tbody>
<tr>
<td>Solve data quality problems in the dataset</td>
<td>(At least 4) Evidences of cleaning erroneous data values</td>
<td>(3) Evidences of cleaning erroneous data values</td>
<td>(2 or less) Evidences of cleaning erroneous data values</td>
<td>(No) Evidence of cleaning erroneous data values</td>
</tr>
<tr>
<td>Integrate appropriate statistical charts for visualization purposes</td>
<td>(At least 4) Intuitive charts and easy to understand</td>
<td>(3) Charts that can be understood</td>
<td>(2 or less) Charts can be improved</td>
<td>(No) Charts are minimal and not intuitive</td>
</tr>
<tr>
<td>Apply suitable data transformation techniques on variables</td>
<td>(At least 4) Show significant relations of quantitative variables</td>
<td>(3) Show relations of quantitative variables</td>
<td>(2 or less) Show important relations of quantitative variables</td>
<td>No relations of quantitative variables</td>
</tr>
</tbody>
</table>

With the rubrics constructed, a scoring strategy can be effectively put in place. For the modules, there is a desired level of skills expected from our learners. Each of the quality definition descriptors occupies one cell in our table and each row represents a particular evaluator criterion. To differentiate the varying quality levels, words from Bloom’s taxonomy or Bigg’s structure of observed learning outcomes are used in our rubrics. These words help to differentiate the varying complex levels of the learning goals. The same weightage of marks can be distributed and totaled to a final score of 25.

At the start of the process, all the members of the judging panel share a common understanding of the assessment rubrics. A ‘calibration exercise’ is carried out and it includes marking a subsample and discussing the agreed marks. In our current assessment grading, feedback is not given. However, to close learning gaps in future, the graded rubrics can be used as a formative class tool to articulate feedback to the respective teams.

Results and Discussion

In this study, we conducted a questionnaire survey comprising of closed and open ended questions on participants’ learning experience, satisfaction and team effectiveness among 25 randomly selected participants.

As shown in Figure 3.0, 80% of participants agreed or strongly agreed that datathon as an assessment tool has helped in their learning experience [Qn.1]. Despite this, 20% of participants preferred not to have datathon as an alternative assessment [Qn.3]. In the open-ended question [Qn.4], students cited their reasons such as the time challenge, difficulties of finding suitable team members and the grading in a datathon. 48% of the participants disagreed the datathon helped them to visualize real world applications, citing reasons that classroom learning is a less stressful mode of learning than a graded datathon where they need to deliver an end-product in such a short time [Qn.5,6]. Finally, a large proportion, 96% of participants agreed they have to collaborate or learn to work in a team for this authentic form of assessment [Qn.7].

Figure 3.0: Survey Question 1: The datathon assessment helps me in my overall learning experience.

Questions 9 to 13 assessed the participants’ opinions on team effectiveness [Qn. 9 - 13] in the
datathon. The team effectiveness is defined as a dependent variable, with suggested independent variables corporative role, work methods, team achievement, commitment and membership suitability [Table 4.0]. Participants ranked the variables based on a 10-point Likert scale ranging from “1” to totally disagree to “10” as totally agree.

Most participants felt team members were committed, cooperative and they experienced team achievement. This is supported by a mean of 7.37 [±2.056], 7.33 [±1.366] and 7.16 [±1.732] respectively. However, students felt members may not develop systematic and effective work methods to solve problems together and there may not be an appropriate balance in every team in terms of a good “mix” of skills: mean of 6.83 [±1.471] and 6.66 [±2.875].

Questions 14 to 19 assessed the participants’ learning from a learners’ perspective [Qn. 14 - 19] in the datathon. Suggested independent variables influencing learners’ learning perspectives are individual development, creative capacity, learning relevancy, real life engagement and satisfaction.

From the results, participant rated satisfaction, learning relevancy and real-life engagement highly: mean of 8.23 [±0.923], 7.67 [±0.517] and 7.50 [±1.049]. Individual development was rated higher than creative capacity: mean of 7.00 [±1.090] and 6.50 [±2.258].

Table 4.0: Means, standard deviations of variables on a sample (n = 25)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Ranked Mean</th>
<th>Standard Deviation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Team Effectiveness</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Team Commitment</td>
<td>7.37</td>
<td>2.056</td>
</tr>
<tr>
<td>Corporative role</td>
<td>7.33</td>
<td>1.366</td>
</tr>
<tr>
<td>Team Achievement</td>
<td>7.16</td>
<td>1.732</td>
</tr>
<tr>
<td>Work Methods</td>
<td>6.83</td>
<td>1.471</td>
</tr>
<tr>
<td>Suitable Membership</td>
<td>6.66</td>
<td>2.875*</td>
</tr>
<tr>
<td>Learning from the learners’ perspective</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Learning satisfaction</td>
<td>8.23</td>
<td>0.923</td>
</tr>
<tr>
<td>Learning relevancy</td>
<td>7.67</td>
<td>0.517</td>
</tr>
<tr>
<td>Real-life engagement</td>
<td>7.50</td>
<td>1.049</td>
</tr>
<tr>
<td>Individual Development</td>
<td>7.00</td>
<td>1.090</td>
</tr>
<tr>
<td>Creative Capacity</td>
<td>6.50</td>
<td>2.258*</td>
</tr>
</tbody>
</table>

Conclusions

As we move towards a holistic conception of assessment as a total package of both learning and assessment, we decide to adopt datathon as a measurement of our students’ learning.

It is observed that the nature of the hybrid datathon contributes to the development of student expertise in data-driven activities such as algorithm thinking, data cleaning and dashboard creation on their datasets. It compels participants to create a feasible end product in an authentic environment and experience team commitment, team achievement and teamwork in the process. The entire process is cognitively beneficial because students sharpen their own self-evaluative capacities in the teams. Building models with data analytics and statistical, mathematical and programming skills in a team setting are important areas of data science for the data analysts. Hence, a datathon provides practical experience among our students in key data value chain and analytics skills. There will be exciting new frontiers in data science for analyst who are involved in computing with data and able to cross subject matter disciplines.

A future area of study is the usage of open data and cross collaboration with organizations in educational datathons. Open data are data repositories that are not subjected to restrictions on their distribution and uses Opportunities of institutes collaborating on datasets for the benefits of communities and public good is a possibility with the advent of “analytics 3.0” organizational analytics. Finally, we can look forward to combination of innovation, analytics and open data in the future.

Acknowledgements

The author wishes to acknowledge the support provided by the management of the School of IIT, Temasek Polytechnic for doing the research work.

References


James, G., Witten, D., Hastie, T., & Tibshirani, R. 2015. An Introduction to Statistical Learning: With Applications in R (6th ed.). New York: Springer.


S. Kumar. (2014) Designing a graduate program in information security and informatics: (MISA). In SIGITE, (pp.141-146) ACM.


W.Cleveland.(2001). Data science: An action plan for expanding the technical areas of the field of statistics. ISI Review, 69:21-26