Measures of Effectiveness (MoEs) for MarineNet: A Case Study for a Smart e-Learning Organization

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Abstract: MarineNet is an US Marine Corps system that provides one-stop shop and 24/7 access to thousands of online courses, videos, and educational materials for the whole Marine Corps. The need for the e-learning organization is to identify the significant capabilities and measures of effectiveness (MoEs) for appropriate e-learning, and then design and identify how to collect and analyze the big data to achieve an effective integration of analytic within the MarineNet learning ecosystem. We show this as a use case and the sample data of the MarineNet CDET website on how to design MoEs that can guide how to collect big data, analyze and learn from users' behavior data such as clickstreams to optimize all stakeholders' interests and results for a typical e-organization. We also show the processes and deep analytics for exploratory and predictive analysis. The framework helps e-organization determine where investment is best spent to create the biggest impact for performance results.

1 INTRODUCTION

MarineNet is an US Marine Corps system that provides one-stop shop and 24/7 access to thousands of online courses, videos, and educational materials for the whole Marine Corps. Many MarineNet courses meet specific Marine Corps training requirements and are extensions of resident schools. Other MarineNet courses are commercially developed and licensed to support individual skill development.

We initially investigated the College of Distance Education and Training (CDET)'s current content management systems (CMS) and their future needs (MarineNet, 2018). The first need is to 1) identify the significant capabilities and measures of effectiveness (MoEs) for appropriate electronic learning (or distance/distributed learning); 2) design and identify how to track this data, and proper analytic techniques to achieve an effective integration of analytic within the MarineNet learning ecosystem. The MoEs of the learning outcomes for MarineNet users reside in the following four specific areas:

- User Profiles
- Courseware
- Video Services
- Site Collaboration

Analytic methodologies are needed in the following areas

- Data Capture
- Dashboard
- Machine Learning
- Predictive analytics

Part of the research questions are listed as following:

1.What constitutes appropriate measures of effectiveness (MoE) for training and education distance learning materials in an enterprise level collaboration learning environment?
2. As a distance learning website with many different stakeholders (e.g., students, instructors, sponsors, and developers), what data need to be collected to support the identified MoEs and support the total value of the website and business processes?
3. What analytic attributes are essential for CDET to collect, analyze, and present useful information in a real-time, intuitive, adjustable, and visual manner (dashboard) to support the identified MoEs?
4. How can the CMS support a dashboard that allows for data manipulation, aggregation, and visualization of identified MoEs?

In this paper, we show how to answer these research questions. Answers to the research questions are related to a broader research area such as data-driven education (Boudett, City, & Murname, 2013;

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Dunlosky, Marsh, Nathan, & Willingham, 2013) clickstream analysis (Nasraoui, Cardona, Rojas & Gonzalez, 2003), effectiveness of online learning or Massive open online course (MOOC, 2019;Kaplan & Haenlein, 2016; Balakrishnan, 2013; Hew, 2016), content management (CMS, 2018), and high level cognition and learning models (Heer, 2010; Kirkpatrick, 2019).

2 DESIGN MEASURES OF EFFECTIVENESS (MoEs) AND DATA COLLECTION

We see the potential for the MarineNet platform to deliver personalized learning including micro-learning--targeted learning either for certain groups, a specific student, or perhaps identified learning styles of the student. The technology can support personalized learning through Experience API (xAPI, 2019)— an e-learning software specification that allows learning content and learning systems to speak to each other in a manner that records and tracks all types of learning experiences. However, the technology isn't the full solution because content must support learning outcomes/objectives and learning must be assessed to measure and improve the learning process. This is accomplished first by designing valid measures of effectiveness (MoEs). To answer the research questions, we studied current learning theories and, using existing and available MarineNet data, designed and selected MoEs to support those constructs based on accepted pedagogical theory and practice as well as on our exploration and evaluation of various deep analytics models.

Initial research identified 36 MoEs, among them, content profiles, student profiles, and student learning behavior are the most important categories as follows:

1 Content Alignment Data.
At the enterprise level, measures of program effectiveness (to a lesser extent learning) are typically tracked by completion rate, GPA, and stated course outcomes or objectives. A CMS must capture this information first. One consideration is that course content must align with the course objectives which could greatly impact the course outcomes (e.g. completion rate and GPA) and provide students suitable learning experiences, appropriate assessment, and measurable progress.

For example, a MoE in this category can compute the correlation of a course content with its predefined objectives. However, this may require text analysis which is out of the initial scope of this project. As an alternative, an instructor could tag the various content such as pre-tests, progress tests, and post-tests with the corresponding learning objectives so that the test scores, GPA, and complete rates can accurately be measured if the learning objectives are achieved. If the instructor is trained to develop objectives/outcomes for higher levels of learning for example, critical thinking can be measured using content tags as well.

2 Student Profile Data.
Measures for learning are often unique to disciplinary fields or individual cohorts or communities. Measuring learning must consider the level of knowledge the student has before the course as compared to after the course, the delta. This delta would then measure the transference of new knowledge not what the student already knows. These MoEs can be supported by a pre-course survey to collect demographic, biographical information. Motivation reflected in the information can significantly enhance retention and transfer and can be the unique differences among individual learners.

3 Student Learning Result Data.
A MoE in this category can be the degree to which targeted outcomes occur as a result of the training, for example, grades, rubric, rewards, GPA, and the number of attempts for competency-based quizzes—i.e. required score of 80%? For example, MarineNet Distance Education Programs and training courses typically use 80% to demonstrate the required knowledge master level.

4 Student Learning Behavioral Data.
Through the MarineNet website, a student can interact with content, instructors, and peers. These interactions can be recorded as student learning behavior data.

The average time and frequency that students access different content are the important measures of student learning behavior. A MoE in this category can be the frequency (or clickstream patterns) for each type of content accessed.

Since an instructor could tag that content (or not) that he or she deems that repetitive learning would be beneficial. MoEs in this category could be aggregated counts or percentages if tagged by objectives or by type of content.

Interaction with instructors with guided practice and timely, formative feedback improves learning and performance. A MoE in this category can be the frequency (or clickstream patterns) for such interactions: the number of times (counts) instructors/students communicate through email (recorded by the system) or forums and blogs. The quality of the interaction is also important for example such as the duration of interaction.

Interaction with other fellow students measures if active participation of the online communities, discussion forums, and group studies exist for a student. Educators indicate there is a strong correlation between learning results and the level of interaction among the students.

With the MoEs and corresponding big data from the website pages (clickstream counts, eyeball time), we apply different types of analytics such as exploratory analysis, visualization in a dashboard, and predictive analytics to discover basic patterns and trends towards a framework for personalized learning as in Figure 1, showing how big data and analytics can be used for personalizing MarineNet learning by recommending personalized materials.

The framework helps CDET determine where investment is best spent to create the biggest impact for learning.

3 IDENTIFY TOOLS

In order to perform data analytics and build machine learning models, we first identified various big data and deep learning tools such as Tableau, Orange, Jump, MATLAB, D3, Python SciPy, Plotly, Pandas, NetworkX, RapidMiner, R, Octave, WeKa, and Google Analytics. We have tested the tools and processes using an open source online learning data set (NIH data set, 2018, consisting of 22 courses, 32K students and daily summaries of student clicks (about 10 million entries).

Since as an organization providing e-learning for a government entity such as the Marine Corps, MarineNet cannot store data in a commercial cloud and therefore requires secure and cost-effective analytics for the continuous analysis of the enterprise. Free and standalone tools are recommended for research and developers can later integrate the research results coded in Python into the production system.

4 DATA EXTRACTION AND PRE-PROCESSING

Part of the MarineNet currently uses Moodle (Moodle, 2019) as the distance learning management system (LMS). We obtained sample data from the existing Moodle system, which does not contain the comprehensive required data elements for MoEs, however, it does include the essential student learning results (part of student profile data) and learning behavior, i.e., the interaction with the website contents for a few courses. We used the data sets to validate part of the MoEs and analytic process to integrate deep analytics including exploratory data analysis, visualization, predictive models with a few machine learning and artificial intelligence models

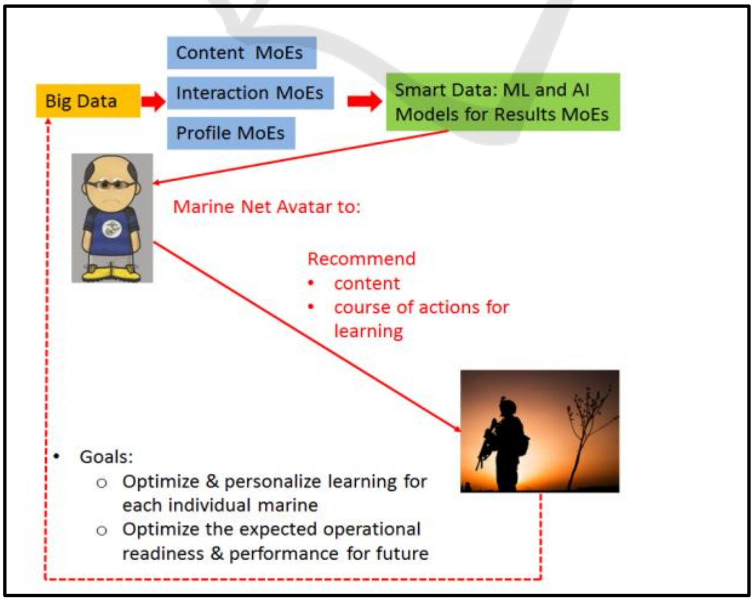


Figure 1: MarineNet avatar to leverage big data and machine learning mdoels for personalizing MarineNet materials.

with an MoE focus. Ultimately the results will indicate to the learner recommended content for an individualized learning path and a course of action for mediation of training objective knowledge discrepancies.

Moodle data from three different classes were used (BCOC 1-19, LCC 1-19, and LCC 3-18). There were two types of data highlighting the student learning behavior (class logs) and student profile (grades) that were extracted. Figure 2 shows an example of class logs and how many events (via different names) were extracted. Figure 3 shows number of events listing what method and how frequent each student interacts with the website. Figure 4 shows the grades data containing the quiz grades and final grade for the class. The grade data also included numbers of forums and discussions participated by students. The class logs and grades were joined using the user names. The user names have been anonymized before any data pre-processing. The final student grade were put into three bins: ‘3’ represents the grades greater than the mean plus one standard deviation; ‘2’ represents the grades between the mean minus one standard deviation and the one plus one standard deviation; ‘1’ represents the grades less than the mean minus one standard deviation; and ‘0’ representing no grade.

Time	User full name	Event name	Description
04/3/19, 05:33	BCOC 1-19_20190403-0533_user_1C	Log report viewed	The user with id '23' viewed the log report for the course with id '133'.
04/3/19, 05:32	BCOC 1-19_20190403-0533_user_1C	XLS grade exported	The user with id '23' exported grades using the xls export in the gradebook.
04/3/19, 05:29	BCOC 1-19_20190403-0533_user_1C	Grader report viewed	The user with id '23' viewed the grader report in the gradebook.
04/3/19, 05:29	BCOC 1-19_20190403-0533_user_1C	Course viewed	The user with id '23' viewed the course with id '133'.
04/3/19, 05:29	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '23' viewed the 'forum' activity with course module id '5868'.
04/3/19, 03:26	BCOC 1-19_20190403-0533_user_1C	Question viewed	The user with id '1182' has viewed the Matching question with id '1117' in the lesson activity
04/3/19, 03:26	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '1182' viewed the 'lesson' activity with course module id '6727'.
04/3/19, 03:25	BCOC 1-19_20190403-0533_user_1C	Content page viewed	The user with id '1182' has viewed the content page with id '1116' in the lesson activity with c
04/3/19, 03:25	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '1182' viewed the 'lesson' activity with course module id '6727'.
04/3/19, 03:25	BCOC 1-19_20190403-0533_user_1C	Question answered	The user with id '1182' has answered the Multichoice question with id '1115' in the lesson act
04/3/19, 03:25	BCOC 1-19_20190403-0533_user_1C	Question viewed	The user with id '1182' has viewed the Multichoice question with id '1115' in the lesson activi
04/3/19, 03:25	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '1182' viewed the 'lesson' activity with course module id '6727'.
04/3/19, 01:38	BCOC 1-19_20190403-0533_user_1C	Content page viewed	The user with id '1182' has viewed the content page with id '1114' in the lesson activity with c
04/3/19, 01:38	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '1182' viewed the 'lesson' activity with course module id '6727'.
04/3/19, 01:38	BCOC 1-19_20190403-0533_user_1C	Lesson started	The user with id '1182' started the lesson with course module id '6727'.
04/3/19, 01:38	BCOC 1-19_20190403-0533_user_1C	Course viewed	The user with id '1182' viewed the course with id '133'.
04/3/19, 00:31	BCOC 1-19_20190403-0533_user_1C	Content page viewed	The user with id '1048' has viewed the content page with id '1136' in the lesson activity with c
04/3/19, 00:31	BCOC 1-19_20190403-0533_user_1C	Course module viewed	The user with id '1048' viewed the 'lesson' activity with course module id '6732'.
04/3/19, 00:31	BCOC 1-19_20190403-0533_user_1C	Lesson started	The user with id '1048' started the lesson with course module id '6732'.
04/3/19, 00:31	BCOC 1-19_20190403-0533_user_1C	Course activity completion updated	The user with id '1048' updated the completion state for the course module with id '6731' for

Figure 2: An example of class logs, how many events (via different names) were extracted.

Username	A file has I	A submiss	Badge listi	Calendar e	Calendar e	Calendar e	Comment	Course act	Course cre	Course mc	Course mc
BCOC 1-19_20190403-0533_user_1(	0	0	0	0	0	0	0	0	0	0	0
BCOC 1-19_20190403-0533_user_1(	5	3	0	0	0	0	352	0	0	0	2
BCOC 1-19_20190403-0533_user_1(	5	2	0	0	0	0	298	0	0	0	4
BCOC 1-19_20190403-0533_user_1(	0	0	0	57	35	28	616	1	38	4	5
BCOC 1-19_20190403-0533_user_1(	5	2	0	0	0	0	437	0	0	0	72
BCOC 1-19_20190403-0533_user_1(	12	4	1	0	0	0	1006	0	0	0	6
BCOC 1-19_20190403-0533_user_1(	6	3	1	0	0	0	407	0	0	0	24
BCOC 1-19_20190403-0533_user_1(	5	1	0	0	0	0	534	0	0	0	2
BCOC 1-19_20190403-0533_user_1(	7	2	0	0	0	0	611	0	0	0	25
BCOC 1-19_20190403-0533_user_1(	5	2	3	0	0	0	538	0	0	0	56
BCOC 1-19_20190403-0533_user_1:	4	2	0	0	0	0	358	0	0	0	6
BCOC 1-19_20190403-0533_user_1:	0	0	0	17	17	0	225	0	20	2	7
BCOC 1-19_20190403-0533_user_1:	10	5	0	0	0	0	665	0	0	0	72
BCOC 1-19_20190403-0533_user_1:	4	3	1	0	0	0	388	0	0	0	13
BCOC 1-19_20190403-0533_user_1:	6	1	0	0	0	0	324	0	0	0	3
BCOC 1-19_20190403-0533_user_1:	5	3	1	0	0	0	364	0	0	0	16
BCOC 1-19_20190403-0533_user_1:	6	3	0	0	0	0	314	0	0	0	8
BCOC 1-19_20190403-0533_user_1:	0	0	0	0	0	0	9	0	0	0	1
BCOC 1-19_20190403-0533_user_1:	0	0	0	0	0	0	0	0	0	0	0
BCOC 1-19_20190403-0533_user_1:	7	2	0	0	0	0	359	0	0	0	33
BCOC 1-19_20190403-0533_user_1:	6	3	0	0	0	0	323	0	0	0	20

Figure 3: Number of events showing the frequency and methods for each student interacted with the website.

Username	Qui	Qui	Qui	Qui	Qui	Qui	Qui	Qui	Qui	Res	Rol	Rol	Rol	Son	Sub	Sub	Sub	Sub	Sub	Sub	Tag	The	The	The	The	Use	Use	Use	Use	Use	Use	Use	XLS	Zip	Quiz	Lessons	Forum	Assignment	Course Total	Grade
BCOC 1-19_20190403-0533_u	15	14	14	16	19	0	0	0	0	0	0	0	0	30	2	6	7	0	0	0	0	37	0	0	1	0	34	0	0	7	0	0	0	7	267.18	1650	25	80	374.23	1
BCOC 1-19_20190403-0533_u	37	15	15	6	23	0	0	0	0	0	0	0	0	20	1	6	18	2	0	0	0	59	0	0	0	0	35	6	0	6	0	0	0	6	280.18	2020.56	42	90	403.62	1
BCOC 1-19_20190403-0533_u	33	16	15	11	24	0	0	0	0	0	0	0	0	23	2	7	12	0	0	0	0	53	0	0	1	0	48	0	0	20	0	0	0	8	282.1	1926.67	48	90	464.83	1
BCOC 1-19_20190403-0533_u	18	15	14	16	21	0	0	0	0	0	0	0	0	13	2	10	14	1	0	0	0	43	0	0	2	0	32	0	0	7	0	0	0	0	312.95	1629.05	17	100	469.59	1
BCOC 1-19_20190403-0533_u	21	14	14	12	21	0	0	0	0	0	0	0	0	15	1	5	7	0	0	0	0	30	0	0	1	0	27	0	0	3	1	0	0	5	288.99	1650	26	130	480.19	1
BCOC 1-19_20190403-0533_u	21	16	16	16	23	0	0	0	0	0	0	0	0	24	3	9	12	2	0	0	0	68	0	0	2	0	48	0	0	4	0	0	0	0	292.31	1960	33	180	503.37	1
BCOC 1-19_20190403-0533_u	30	14	14	18	23	0	0	0	0	0	0	0	0	14	1	6	13	1	0	0	0	67	0	0	2	0	31	0	0	5	0	0	0	1	279.1	1876.67	46	177	506.73	1
BCOC 1-19_20190403-0533_u	19	14	14	16	27	0	0	0	0	0	0	0	0	25	1	6	8	0	0	0	0	49	0	0	2	0	36	0	0	4	0	0	0	1	290.53	1910	33	170	506.88	1
BCOC 1-19_20190403-0533_u	24	15	15	12	19	0	0	0	0	1	0	0	0	20	1	8	11	1	0	0	1	36	0	0	3	0	30	3	0	4	2	0	0	3	299.25	1766.67	27	170	508.41	1
BCOC 1-19_20190403-0533_u	22	15	15	12	21	0	0	0	0	0	0	0	0	18	1	6	14	3	0	0	0	53	0	0	3	0	35	1	0	2	0	0	0	2	304.06	1960	44	130	508.58	1
BCOC 1-19_20190403-0533_u	20	14	14	11	20	0	0	0	0	0	0	0	0	24	2	7	10	3	0	0	0	55	0	0	5	0	44	0	0	5	0	0	0	2	264.39	2126.67	29	80	517.14	1
BCOC 1-19_20190403-0533_u	17	15	15	17	22	0	0	0	0	0	0	0	0	21	1	8	8	2	0	0	0	44	0	0	1	0	32	1	0	0	0	0	0	0	306.17	2023.33	27	80	517.46	1
BCOC 1-19_20190403-0533_u	33	17	17	17	26	0	0	0	0	0	0	0	0	25	2	7	19	7	0	0	0	85	0	0	7	0	38	0	0	4	0	0	0	4	268.49	1943.33	52	140	519.17	1
BCOC 1-19_20190403-0533_u	33	15	15	12	24	0	0	0	0	0	0	0	0	35	2	7	9	0	0	1	0	90	0	0	2	0	48	9	0	20	0	0	0	8	269.45	2082.22	32	165	536.06	2
BCOC 1-19_20190403-0533_u	23	14	14	6	21	0	0	0	0	0	0	0	0	34	2	7	11	1	0	0	0	43	0	0	2	0	33	16	0	12	0	0	0	0	267.21	2076.67	37	150	541.24	2
BCOC 1-19_20190403-0533_u	39	15	15	15	21	0	0	0	0	0	0	0	0	23	2	8	9	0	0	0	0	##	0	0	2	0	44	0	0	3	0	0	0	6	277.38	2093.33	41	150	547.26	2
BCOC 1-19_20190403-0533_u	32	15	15	21	27	0	0	0	0	0	0	0	0	14	1	7	11	2	0	0	0	51	0	0	2	0	42	0	0	5	0	0	0	0	265.54	2126.67	48	155	550.79	2
BCOC 1-19_20190403-0533_u	22	15	15	9	18	0	0	0	0	0	0	0	0	19	1	7	8	0	0	0	0	59	0	0	2	0	41	1	0	6	0	0	0	1	316.37	1956.67	26	170	552.34	2

Figure 4: The grades data contain the quiz grades and final grade for the class. They also included numbers of forums and discussions participated by students. The class logs and grades were joined.

5 EXPLORATORY DATA ANALYSIS (EDA)

The dataset included three MarineNet courses consisting of events such as "content page viewed." Event logs and grades were merged by user name. Logs and grades from the three different courses were used. Number of events per user were listed and basic relationships between events were compared to performance (learning) as measured by final grade which is used as the dependent variable. The candidate independent attributes (student activity) included:

- File uploaded
- A submission submitted
- Comment created
- Content page viewed
- Course module viewed
- Course viewed
- Discussion viewed
- Post created
- Question answered
- Some content posted
- status of submission viewed
- …

Total about 120 of the different events and aggregated attributed were extracted from the data.

The four independent variables of student activity selected for initial EDA: *Content page viewed, Course module viewed; Course viewed, and Discussion viewed*. These four attributes had the highest coefficients of variation (CV) and were selected because the higher variability may be the source of variability with student grades and therefore possibly correlated. Those other variables with lower CVs and very narrow dispersion about the mean, with almost zero SD, would unlikely result in meaningful correlations with course grades.

The example below uses the data set BCOC1-19 since it has the greatest number of students (84 total students and 64 had grades in the end of the class).

Tableau.

Tableau is a cloud-based business intelligence for enterprises (Tableau, 2019), which allows many different views and visualizations of a data set. We used a desktop version of Tableau which is limited in terms of big data size and does not use cloud computing.

Figure 5 shows a Tableau view of number of specific events (size of the rectangles and final grades (color) for each student. Different learning behavior exhibited here: Student 8826 has a higher grade (darker) and large number of events of "Course viewed" and "Course module viewed;" Student 6466 has a lower grade (lighter), however fewer number of events of "Course viewed" and "Course module viewed;" Student 2293 has a higher grade (darker), however, fewer number of "Course viewed."

Sankey.

Sankey diagrams (Sankey, 2019) are a specific type of flow diagram, in which the width of the arrows is shown proportionally to the flow quantity. This extends the capability of the Tableau view above to view and visualize more attributes in the data set.

Figure 6 shows a Sankey plot for a class log. The attributes from left to right are "user name," "component," "event name," and "grades". There are 6.91k events linking "Course module viewed" and "3 (Grade > mean + std)." The graph shows initial correlation between the higher grade (3) and the learning behavior "Course module viewed."

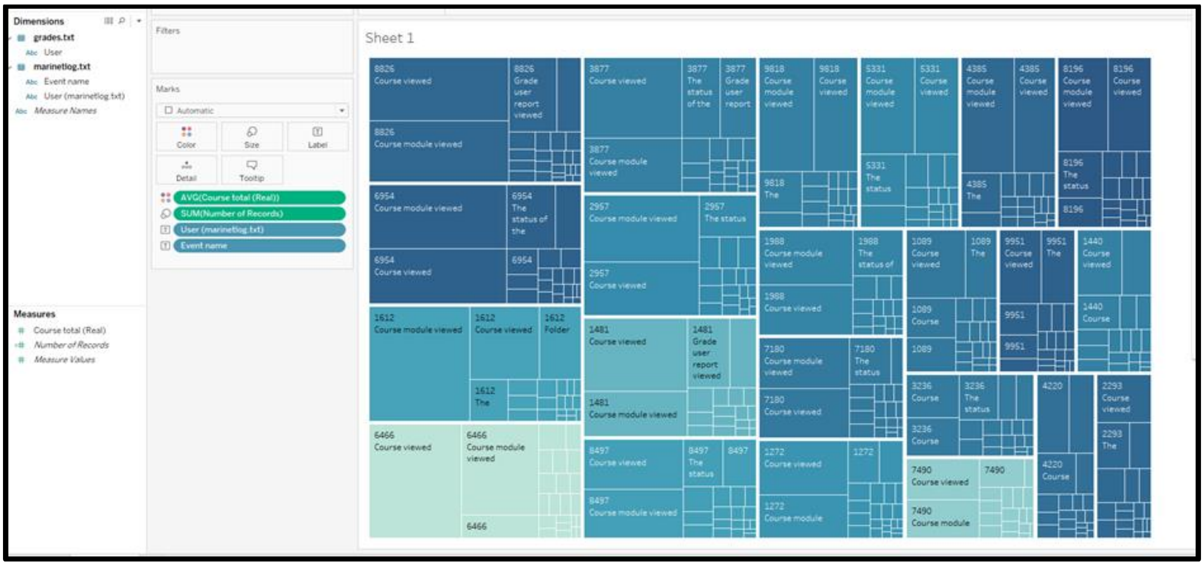


Figure 5: A Tableau view shows number of specific events (size of the rectangles and final grades (color) for each student. Different learning behavior exhibited: user 8826 has a higher grade (darker) and large number of events of “Course viewed” and “Course module viewed;” Student 6466 has a lower grade (lighter), however fewer number of events of “Course viewed” and “Course module viewed;” Student 2293 has a higher grade (darker), however, fewer number of “Course viewed”.

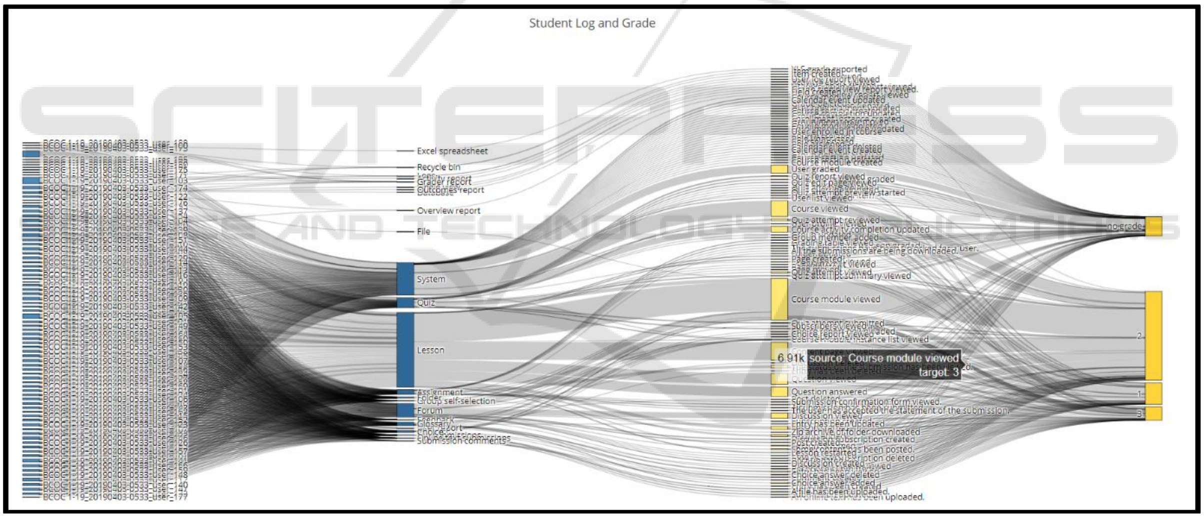


Figure 6: Sankey plot for a class log. The attributes from left to right are “user name,” “component,” “event name,” and “grades”. There are 6.91k events linking “Course module viewed” and “ 3 (Grade > mean + std)”.

MATLAB.

Exploratory analysis tools included MATLAB (Matlab, 2019), Excel Analysis ToolPak and the open source tool, Orange. MatLab includes multiple regression as well as other powerful exploratory tools but for an educational analyst the Excel Analysis ToolPak provides a quick an easy way to initially explore the data. Multiple regression analysis of the four attributes with the dependent variable of final course grade resulted in an R square of .13 and an adjusted R square of .08. Simple regression shows “*Course Viewed*” with the highest R Square of .12 (adjusted R square of .11) which is low but it is intuitive that one must view the course more than once to learn the content (at least for some students. There were only 65 observations and the analysis goal was to demonstrate how generated data from an LMS could be initially analyzed. Figure 7 is an Excel residual plots which shows a probable non-randomness suggesting a better fit for a non-linear model.

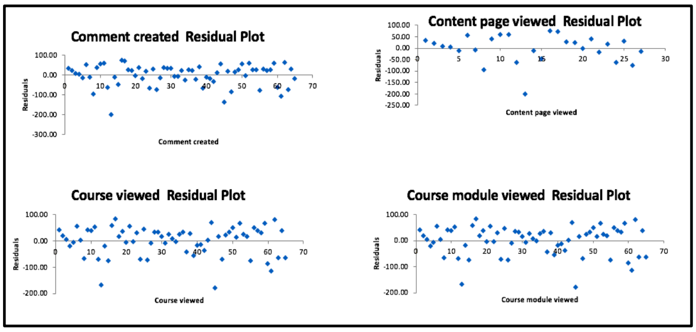


Figure 7: Excel residual plots.

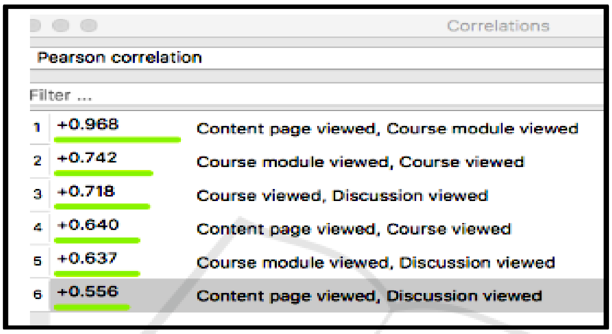


Figure 8: Orange Tool (Pearson correlation).

Orange.

Another exploratory tool used was Orange (Orange, 2019). It features a visual programming front-end for explorative data analysis and interactive data visualization. Orange consists of data and pre-processing tools including importing relational and unstructured databases, filtering, merging, data sampler, and discretizing. Visualizing tools include statistical functions such as box plots, distributions, scatter plots, and heatmaps. Orange includes implementations of many advanced statistical and machine learning algorithms such as linear and logistic regression, decision trees, naïve Bayes, random forest, and neural networks. One useful data tool in Orange is Pearson's correlation, which quickly identifies correlations between many attributes. Figure 8 shows "content page viewed" and "course module viewed" are almost synonymous and therefore one or the other could probably not be used in the analysis.

6 PREDICTIVE MODELS

In order to improve online learning to help students achieve the best results, we need to predict a student's end result (e.g., report) before the end of the class, identify the reasons for predictions, and then send early warnings or personalize the content so the student can improve their behavior or obtain more personalized content, and therefore receive better learning results.

Figure 9 shows an Orange workflow for building typical machine learning models including decision trees (Weka, 2019), neural networks, kNN, naive Bayes, and logistic regression for predictive models of grades. Figure 10 shows the decision tree output for the total 83 students in BCOC 1-19. The goal of a predictive model is to predict grade level 1, 2, and 3 based on the students' interactions/activities (events) in the website, where 1: total grade scores <520, 2: 640> total grade scores>520; 3: total grade scores >640. The decision rules for the two green box (i.e., the highest grade bin "3") are as follows

- "Number of events for a file uploaded >0", "course viewed >395," "Quiz attempt submitted >15;"
- "Number of events for a file uploaded >0", "course viewed >395," "Quiz attempt submitted <=15," "Course viewed <=406."

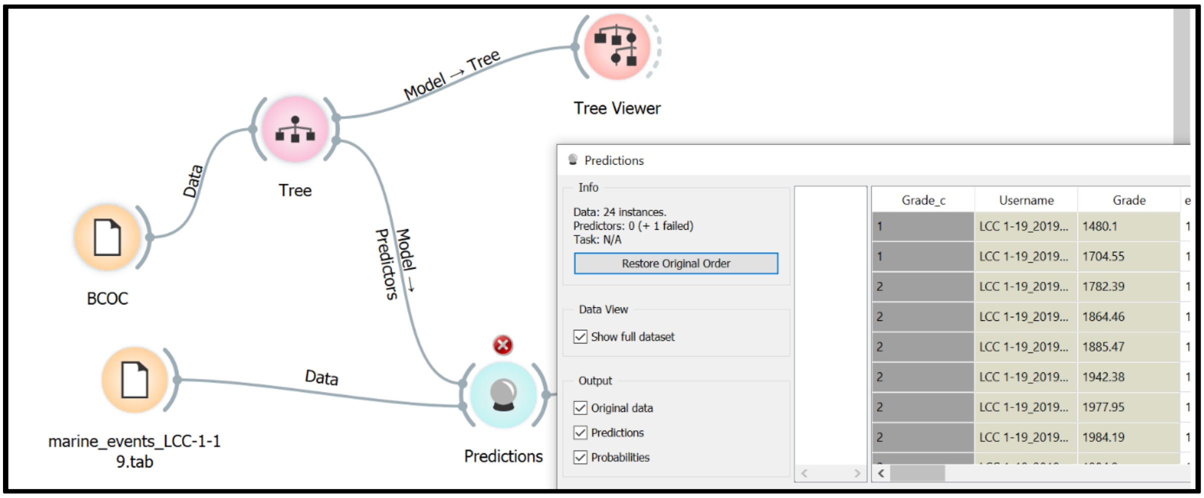


Figure 9: An Orange work flow for building models.

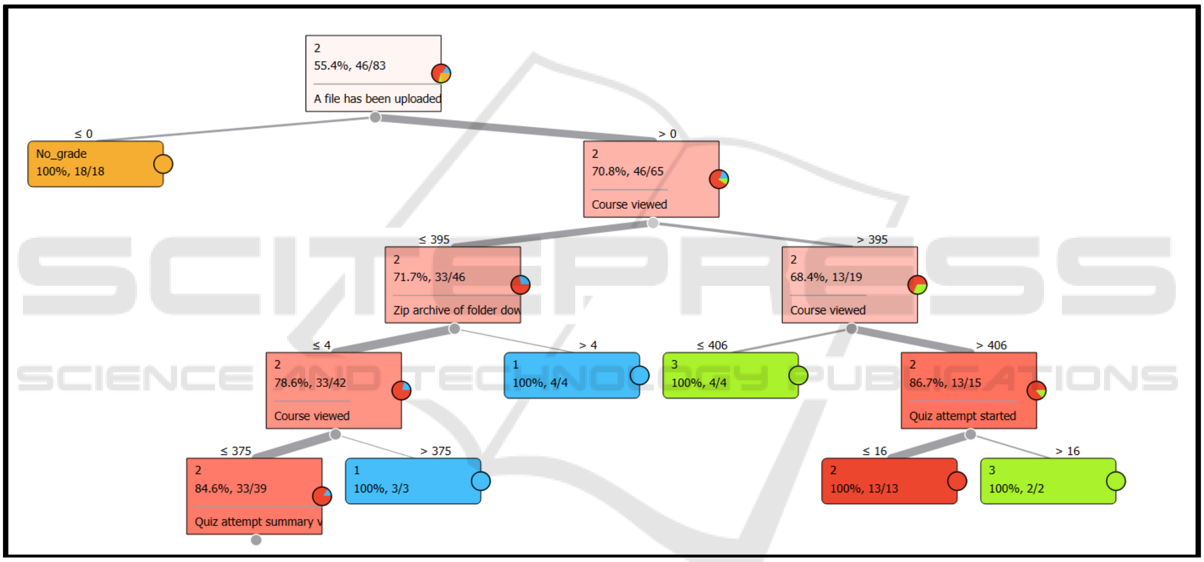


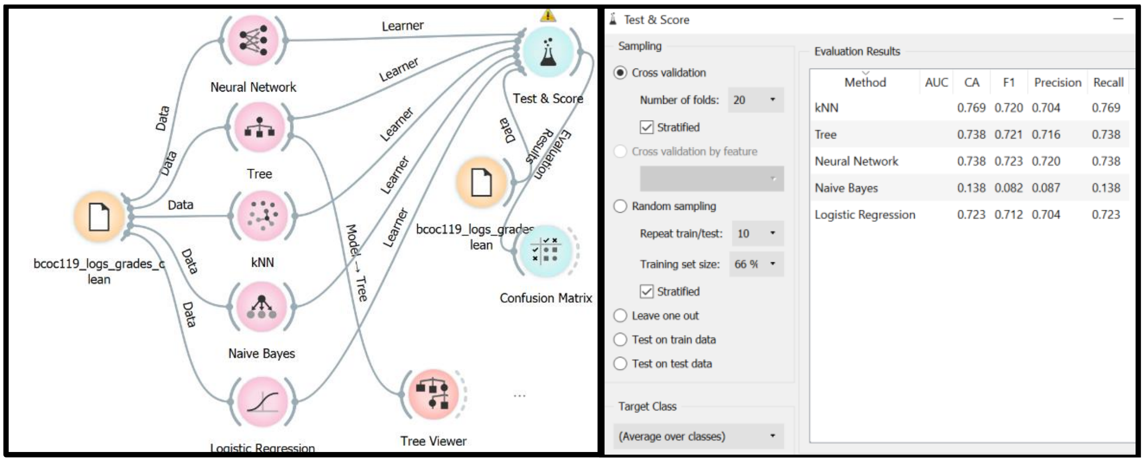
Figure 10: The decision tree output for the students in BCOC 1-19. The decision rules for the two green boxes (i.e., the highest grade bin "3") are 1) "Number of events for a file uploaded >0", "course viewed >395," and "Quiz attempt submitted >15;" 2) "Number of events for a file uploaded >0", "course viewed >395," and "Quiz attempt submitted <=15," "Course viewed <=406".

The decision rules for the two blue boxes (i.e. the lowest grades bin "1") are listed as follows:

- "Number of events for a file uploaded >0", "course viewed <=395," and "Zip archive of folder downloaded > 4;"
- "Number of events for a file uploaded >0", "course viewed <=395," "Zip archive of folder downloaded <= 4;" and "Course viewed >=375."

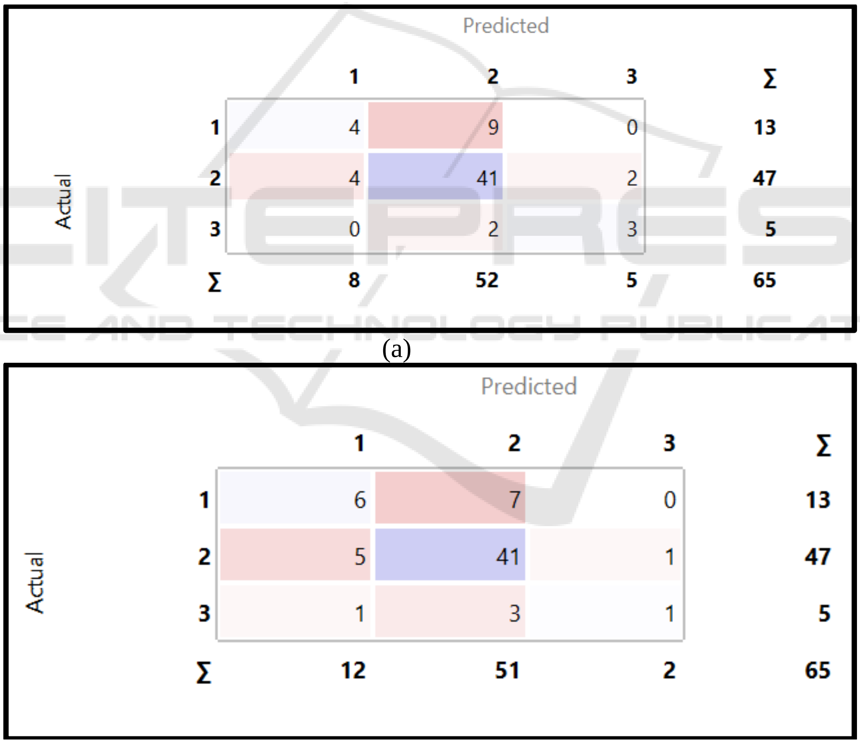
Note that the rules for the low performers compared to the high performers seem different in terms of the attributes "Course viewed" and "Zip archive of folder downloaded." The zip archive could be the quiz materials on which the students tried to work. Proactive actions may be taken, for example, to remind students to finish the quizzes on time before they attempted too many times. The decision trees algorithm automatically discovered the rules and thresholds used in the rules.

The question is that if these rules apply to the test set (e.g., LCC-1-19 in Figure 9). We scored the test set using the output rules from the training set (i.e., BCOC-1-19) to generate predictions of high (3), low (1), and average grades (2) for the students in this class and then compared the predictions with the ground truth.



(a) (b)

Figure 11: (a) An Orange work flow for building multiple predictive models; (b) Test & Score shows a 20-fold cross-validation of classification accuracy (CA), precision (% of true positives out of predicted), recall (% of true positives out of actual).



(a)

Actual \ Predicted	1	2	3	Σ
1	4	9	0	13
2	4	41	2	47
3	0	2	3	5
Σ	8	52	5	65

(b)

Actual \ Predicted	1	2	3	Σ
1	6	7	0	13
2	5	41	1	47
3	1	3	1	5
Σ	12	51	2	65

Figure 12: (a) Confusion matrix of the cross-validation model for the decision trees method; (b) Confusion matrix of the cross-validation model for the neural network method.

Since the number of students in each class is low and the classes are quite different, a low accuracy of test prediction is expected. Nevertheless, the machine learning algorithm can pick up more relevant attributes.

We examined more predictive methods using class BCOC-1-19 data and taking out 18 students without grades which left only 65 students in the data set. We used the cross-validation method for these predictive models which splits the data into a given number of folds (20 folds in this case).

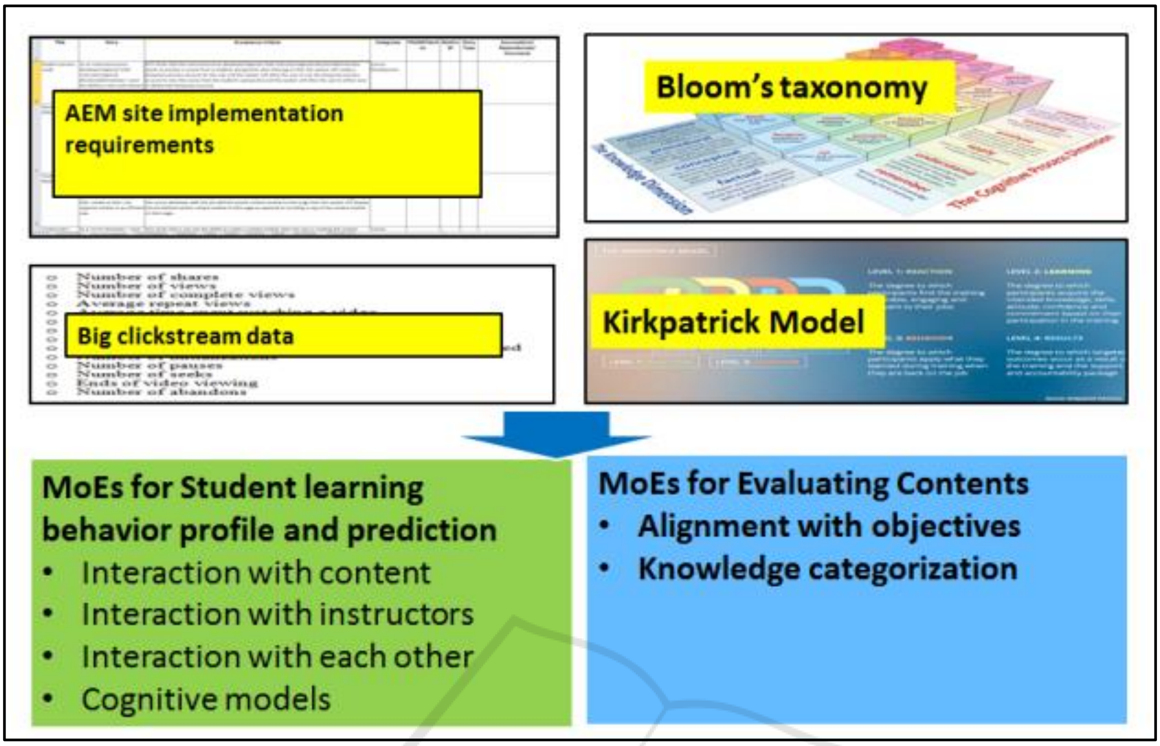


Figure 13: Future work combining contents and learning models.

The algorithm is tested by withholding examples from one fold at a time; the model is induced from other folds and examples from the held out fold and classified. This is repeated for all the folds (Orange, 2019). The fused grades and logs result in 119 variables in total. Figure 11 (a) shows the Orange workflow for multiple predictive models. Figure 11 (b) shows the a 20-fold cross-validation results of classification accuracy (CA), precision (% of true positives out of predicted), recall (% of true positives out of actuals) for multiple predictive models. The predictive models have similar results except the naïve Bayes method. Figure 12 (x,y axes grade level) shows detailed confusion matrices for the decision trees (a) and neural networks methods (b). The decision trees method has a better confusion matrix (errors confuse "2" with "3" and "1" and "2") than the neural networks method only predicted 20% correctly for the grade level 3.

7 DISCUSSION

We show an example using the sample data of the MarineNet CDET website on how to design MoEs that can guide on how to collect big data, analyze online behavior data such as clickstreams correlated with performance assessment data, therefore measure and improve all stakeholders' interest and results for an e-learning organization. Many of the analytical tools indicate that useful analytics and predictive power can be derived from website logs and assessment data. To extend the project for a future prospective for distance e-learning and the MoEs we develop in this project, one can leverage more technology to support personalized learning and collect student learning behavior data such as Experience API (xAPI, 2019).

More challengingly in terms of measuring how students learn, we could use more content based MoEs which are not of the focus of this paper. The related subset of MoEs were based on accepted pedagogical theory and practice as well as on our exploration and evaluation of various learning models that may measure learning or training or at least measure some of their correlations. For example, how to measure Bloom's Taxonomy (Heer, 2010) related data, which classifies learning into factual, conceptual, procedural, and metacognitive and the subsequent cognitive dimensions required, and it is a classic learning model and very in use today. MoEs related to the Kirkpatrick Model (Kirkpatrick, 2019) focus on the degree the learner interacts with the content in each of the four levels, for example, 1) Reaction: degree to which training is favorable, engaging and relevant to their jobs; 2) Learning: degree to which participants acquire intended knowledge, skills, attitude, confidence and commitment based on their participation in the training; 3) Behavior: degree to which participants apply what they learned during training; 4) Results: degree to which targeted outcomes occur as a result of the training. Figure 11 shows a holistic view of potential future work of the integration of the concepts and models for total personalized smart online learning leveraging big data and machine learning.

8 CONCLUSION

We show a use case using the sample data of the MarineNet CDET website on how to design MoEs that can guide how to collect big data, analyze website behavior data such as clickstreams with performance assessment data, therefore measure all stakeholders' interests and results for an e-learning organization. We also show the processes and tools for exploratory and predictive analysis.

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