

Measuring the Usability of Learning Content in a Web Based Learning Management System Course– A Statistical Approach

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ABSTRACT: The rise in data consumption has risen drastically. It is an understatement to suggest that users may have difficulty in finding data and are often clueless about how to put these contents to optimal use. A content based system needs to be rated on the utility function of its contents. In this paper the author has made an attempt to determine the best way to calculate the utility function of a learning content using collaborative filtering. The research question was that, is there any significant difference between the average marks of the two groups, if one group was ratings the contents but not provided any recommendations and the other was receiving the recommendations provided by the first group. The second research question was to find if there is a relation between average ratings earned by each content and average number of view earned by it. In the experiment I verified using independent sample t-test that there is a significant difference between the average marks scored by the two groups. I also developed a regression model to predict the average views earned by a learning content based on the ratings earned by it. Using Spearman Rank Correlation Coefficient I verified that there is a relation between average ratings earned by each content and average views earned by it.

KEYWORDS: Recommendation, recommender, algorithms, utility function , explicit and implicit ranking, statistical approach

I. INTRODUCTION

Learning management systems today have huge amounts of learning material [1]. The recommender systems that we know today are all variations of a certain group of web applications which were designed to create a solution to solve the problem of overload faced by users who are connected to various information sources be it print, internet, visual or audio media sources. Hence, items with similar content to the current viewing item will be recommended to the active user [2]. Instead of the user reaching out to information, the information now has to reach out to connect to the user who is searching for it. RS is that a good way to personalize recommendations for a user is to identify people with similar interests and recommend items that have interested these like-minded people [3]. [4] proposed that learner opinion and feedback is crucial for learning materials need to be placed in a learning management system. We have proposed an approach to build a software agent that uses data mining techniques such as association rules mining in order to build a model that represents on-line user behaviours, and uses this model to suggest activities or shortcuts. These suggestions can help learners better navigate the on-line materials by finding relevant resources faster using the recommended shortcuts and assist the learner choose pertinent learning activities that should improve their performance based on on-line behaviour of successful learners. In 2015, it is estimated that information intake will rise to 75 GB from an earlier study in 2006 which measured the information take to be more than 400 MB. Recommendation systems are the strength for the e-commerce sites on the net today likes Netflix, Amazon, e-Bay etc. In every content based system, there will be several cases where the content is under-utilized simply because the user is not aware of its presence as the utility of the content is not known [5]. This is called the utility function of content in recommendation systems. Learning management systems (LMSs) are becoming increasingly popular at many educational institutions such as universities. However, they provide same content for all learners in a given course. [6]. With advances in technology, learning methods and objects have evolved from conventional text based content to multimedia and interactive knowledge objects. Learning objects can be useful for tutors and learners; however, there are some limitations to

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sharing of learning objects across many platforms to benefit respective learners [2]. As discussed in [3] most of the existing systems ignore gauging the students' engagements levels and mapping them to suitable delivery needs which match the students' knowledge and preferred learning styles. Though deluge of learning material is very difficult for learners to handle and that may be one of the reasons for a course module in a Learning Management System to fail in meeting learner's expectations [6].

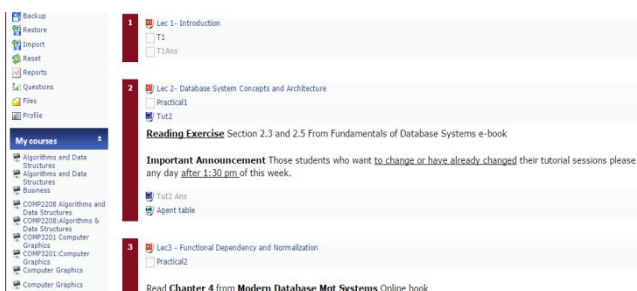
II. NEED FOR RECOMMENDERS IN LEARNING MANAGEMENT SYSTEMS

Recommender systems for educational purposes need to be integrated in course management systems as they help users to streamline their learning paths in the case of a student, whereas in the case of a teacher to prepare an course webpage that will have the most suitable content oriented to providing guidelines on usage of the course contents in the registered course.

However the challenge lies in the ways to extract the suitable learning material and present it to learners.

In Figure 1 – a regular course webpage is shown that lists all the learning material.

- The webpage must have the following information.
- The contents need to be more descriptive.
- The type of content – theoretical, graphic,
- A summary about the material listed.
- The number of figures and programming examples available in the material



(a)

Activity	Views
News forum	59
Course Profile	200
Sample exams - Solved	459
Week 1	
Read your Textbook Online	535
Week 2	
Lec 1	368
Tut 1	500
Practical 1	453
Week 3	
Lec 2	200
Tut 2	311
Practical 2	488
Trial Quiz	8

(b)

Figure 1 – Course webpages (a) a typical online course webpage in a Course Management System (b) Screenshot of the activity posted by the teacher and the number of views received from the group

III. DISCUSSION

Discerning the value of the utility function of the content object is the prime concern for recommendation systems and it is normally referred to as the recommender problem. The system is based on the following assumption that the recommendation for each content object in the recommendation system needs to be calculated on the basis of the following inherent factors:

- Users interested in the same content- course name, course topics, course belongs to some specialization common to same learners
- Items liked by users with similar interests - learning material similar in nature – topic name, keywords
- Rating earned - The content is available with information about the ratings it earned during its life history within the content system.
- Recommendation based on users locations

Educational institutions host dedicated learning management systems that contain a humongous quantity of educational and instructional content. The availability of a various types of content and plethora of platforms to make it available to learners has created a very large multitude of learning content easily available at the very few clicks.

Learners have no dearth of learning material however the deluge of material is difficult for most learners [10]. The challenge faced by learners in most cases is the

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- Time Constraint – course assessments to be completed within given time.
- Material access – access the relevant learning material to complete the course assessments successfully
- Content magnitude – Large and expanding volume of learning material.
- Lack of interactive features – The learning material may not be interactive enough to sustain the interest of the learner.
- Lack of usability feedback – The items in the learning management system is not checked for usability. Peer feedback is not recorded formally. Students depend on their experiences to build their learning experiences.

The problem is how to get the system to find and recommend the optimum learning content for each user visit. The aim is to design a system that will help the teacher to improve the course contents and their use by guiding the students to materials filtered after taking into consideration their interest in the learning material measured by the clicks and visits made by the learners while perusing the collection.

IV. EXPERIMENTAL RESULTS

The figures 2 and 3 shown above suggest that the content put up by the teacher needs evaluation about the relevance or utility as these contents are not supported by details such as type of learning material (audio, video or textual), it also does not have a summary about the contents of the material, its intended use or suitability for the learner group it is intended for, The best or optimum learning content is dependent on whether it is the most relevant (relevance) latest on the topic (freshness) interactive types of media (audio, video, textual, images) The best learning object also gets maximum views, maximum duration time, maximum ratings, and maximum number of users. We propose to use a statistical method, wherein the utility function of data from a dataset can be ascertained from the underlying data. For instance, based on a set of course web pages that were rated as "relevant" or "irrelevant" by the user, the naive Bayesian classifier can be used to classify unrated course web pages. However this requires creating content clusters that will direct users to the most suitable material for their study. Learning items or materials – course names, chapter readings for each course, examples on the topic, updated online material or references, links to online material.

Context of use – course name, topics in course profile, learning management systems, Selection metrics -Quality of the learning material based on number of recommendations measured using views and recommendations., ratings received from learners Popular ranking methods are content undergoes a transformation from being available and searched for to being found and recommended to learners who need it. This discovery of content is based on a ranked list of learning contents ranked by the ratings provided.

The methodology adopted in recommender systems involving large numbers of items, their rankings and their users is to adopt a hybrid approach based on collaborative and content-based recommender system. The KNN algorithm approach depending on implicit (we learn or infer from user clicks and ratings) and explicit (user says what he or she likes) feedback.

In the user to user version, kNN executes the following three tasks to generate recommendations for an active user: (1) determine k users neighbors (neighborhood) for the active user a; (2) implement an aggregation approach with the ratings for the neighborhood in items not rated by a; and (3) extract the predictions from in step 2 then select the top N recommendations.

We propose to identify the highly recommended learning object by studying the ratings received A metric or a Similarity Measure (SM) determines the similarity between pairs of users (user to user CF) or the similarity between pairs of items (item to item CF).

For this purpose, we compare the ratings of all the items rated by two users (user to user) or the ratings of all users who have rated two items (item to item).

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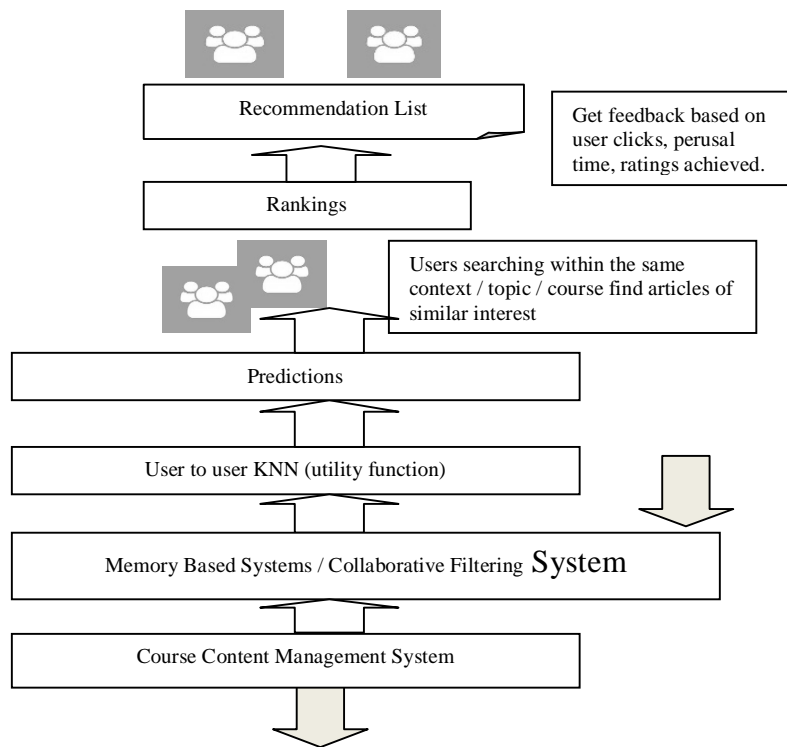


Figure 3 – A typical online course webpage in a Course Management System.

The kNN algorithm is based essentially on the use of traditional similarity metrics of statistical origin. These metrics require, as the only source of information, the set of votes made by the users on the items (memory-based CF). Among the most commonly used traditional metrics we have: Pearson correlation (CORR), cosine (COS), adjusted cosine (ACOS), constrained correlation (CCORR), Mean Squared Differences (MSD) and Euclidean (EUC) [9]

Most recommendations are presented in a sorted list. Recommendation can be understood as a ranking problem [7,8]

- Popularity is the obvious baseline
- Ratings prediction is a clear secondary data input that allows for personalization

The following features can be added

- Ranking items by ratings received (Rr)
- Ranking items by number of views (Rv)
- Ranking items by view time (Rt)

The experiment was conducted on two groups of learners. In one group the learners were provided with normal set of learning materials for 10 weeks of a course. The learners in the first group were asked to peruse the material and provide a rating for each week for each content provided in the course.

The ratings provided by these students were made available to the next set of enrolled students to use as recommendations. For the first group a link was provided at the end of each course material with the ratings (a Likert scale) from using which the average ratings earned were collated per content and these ratings were then exported to the recommender module for the second group. However they did not receive the average score or views or recommendations

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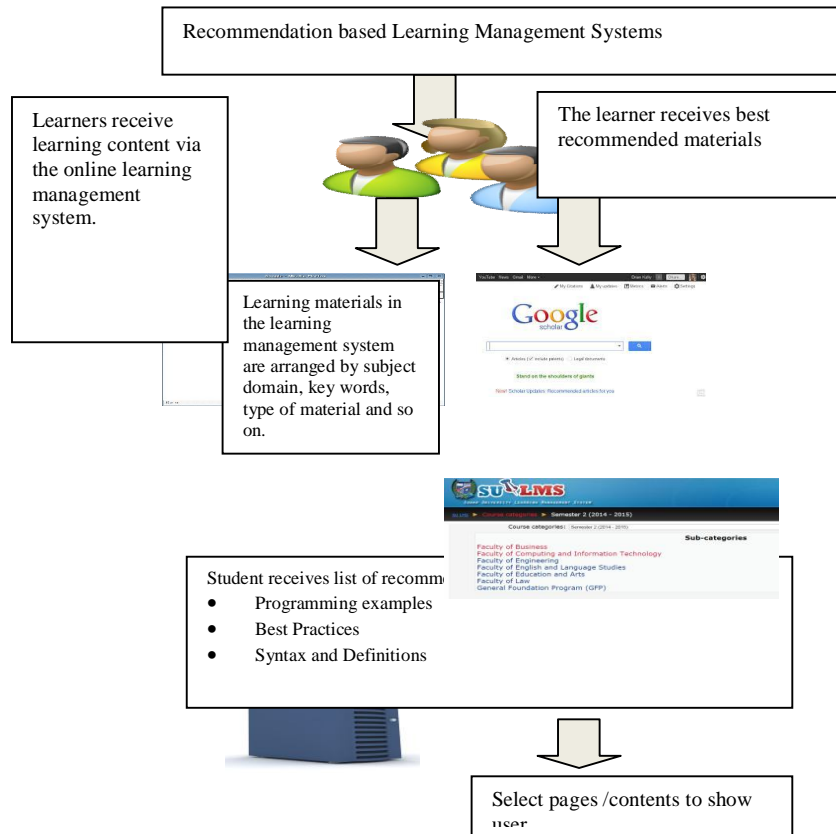


Fig 4 – Flow of recommended learning material

The contents were segregated into two three fragments on the basis of the book source on which they were based. The lecturer could select the books based on his course profile which lists the selected textbooks and references. Hence we selected 3 learning contents from three learning sources (here selected books as mentioned the course profile) for 10 weeks. The contents were fragmented into theoretical, tutorial and practical material. Hence total of 90 learning fragments were there in the online learning resource set for the course. The large learning resource set was difficult for most students to peruse without a proper guiding or recommending mechanism.

The views earned by each content from the second group was the only way to know the popularity. Using t-test we can check if there is a significant difference in the average marks earned by the students of the first group and the second.

Using Spearman Correlation coefficient we can ascertain the relation between average ratings earned by each content and average views earned by it.

Using Rank Correlation coefficient we can define that there is a relation between average ratings earned by each content. Using Regression Analysis we can predict the number of views which can be earned by content depending on the ratings given.

Table 1 and Table 2 describes the two groups, sample size 30, and the result derived which indicates that Levene's Test for Equality of Variances provides that the Sig. value is > 0.5.

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Table 1 - Group Statistics

Grp	N	Mean	Std. Deviation	Std. Error Mean
Marks 1	30	47.9000	19.79612	3.61426
Marks 2	30	58.4000	17.82985	3.25527

Table 2 - Independent Samples Test

		Levene's Test for Equality of Variances			t-test for Equality of Means					
		F	Sig.	t	Df	Sig. (2-tailed)	Mean Difference	Std. Error Diff.	95% Confidence Interval of the Difference	
									Lower	Upper
Marks	Equal variances assumed	.696	.408	-2.159	58	.035	-10.50	4.864	-20.23	-.763
	Equal variances not assumed			-2.159	57.38	.035	-10.50	4.864	-20.23	-.761

So the variance in this population are roughly equal, t-test for independent Groups G1 and G2 and their total Marks , G1 – without recommended contents ,G2- with recommended contents.

Table 3– Correlation between Total Views and Average rating

		Avg ratings	Avg. no. of views
Avg ratings	Pearson Correlation	1	.807
	Sig. (2-tailed)		.000
	N	90	90
Avg. no. of views	Pearson Correlation	.807	1
	Sig. (2-tailed)	.000	
	N	90	90

** . Correlation is significant at the 0.01 level (2-tailed).

The Correlation Table show in Fig 5 that there is a high correlation between the average ratings and number of views, and it is significant at 0.01.

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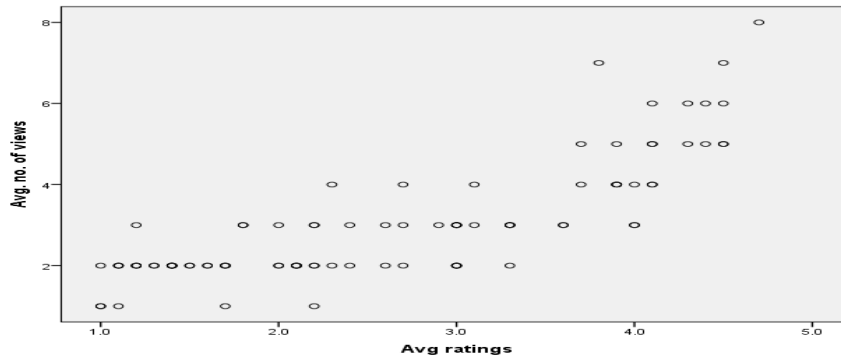


Figure 5- The Scatter Plot Graph average Ratings with average Views

This graph indicates that there is a positive relation between the average rating earned by the content from the first group and the views received from second group.

R is the Correlation Coefficient; R Square indicates that 65.2% of the variance is explained by the model.

The ANOVA regression table shown below, indicates that the regression model is significant i.e. $p < 0.05$

Table 5 - ANOVA^a

Model	Sum of Squares	df	Mean Square	F	Sig.
1 Regression	72.697	1	72.697	164.546	.000 ^b
Residual	38.879	88	.442		
Total	111.576	89			

a. Dependent Variable: Avg ratings

b. Predictors: (Constant), Avg. no. of views

Table 6 - Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	.798	.161		4.950	.000
1 Avg. no. of views	.614	.048	.807	12.828	.000

a. Dependent Variable: Avg ratings

From Table 2, $t(58) = -2.159$, $p < 0.05$. Therefore the test is considered significant at the 0.05 level. This substantiates our assumption that there is a significant difference between the average marks of the groups.

From Table 3 the value of correlation coefficient R between number of ratings attributed to group 1 learner and views attributed to group 2 learner is 0.807 and is significant at 0.01. This is highly co-related.

From Table 6, Coefficients Table, we can get the predicted number of views = $0.798 + 0.614 * \text{Avg ratings}$

V. CONCLUSION

I have proved that there is significant difference between the average marks of the two groups, of one group was ratings the contents but not provided any recommendations and the other was receiving the recommendations provided by the first group. The second research question was to find if there is a relation between average ratings earned by each content and average view earned by it.

I have also verified that using independent sample t-test that there is a significant difference between the average marks scored by the two groups.

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I also developed a regression model to predict the average views earned by a learning content based on the ratings earned by it.

Using Spearman Rank Correlation Coefficient I verified that there is a relation between average ratings earned by each content and average views earned by it.

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