CAHIERS MAGELLANES-NS
Volume 06 Issue 2
2024

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
http://magellanes.com/

EVALUATION OF ONLINE MOOC COURSES AND SUPPORT FOR LEARNERS' COURSE SELECTION

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ABSTRACT

After the pandemic circumstance, the education has tremendously changed the way in education through online. Millions of new clients have signing up on Massive Open Online Course (MOOC) providers, such as Coursera or edX, online platforms because it is standardized and decentralized system in online education. Hence, the important and curiously investigate areas in online instruction in this last decade is Personalized Group based recommendation system since the learning fashion is particular with each student. The objectives of this study investigate and legitimize the significance of students' execution in online course materials in a real-world education system by assessing data utilizing data mining techniques. Several techniques and algorithms in Data mining are used to identify the preferences of accessible a huge number of learning modes of a client in a system. Based on individual and other learners' behaviours, searches and past history, we are able effectively identify the proposals by Recommender system. This strategy can predict preferred modes of learning for a learner and after that recommends the most excellent modes of learning to a learner. The result of the investigation display how extricated learning helps in improving decision making processes. The scope of this study is to recognize the components that affect the students to select the materials of online courses in pre-graduate education. An early desire of student performance makes a move for better achievements of the student. To achieve standard quality education, a few attempts have been made to expect the performance of the student. Especially Prediction Techniques, Using data mining tools, such as Recommender System and Content-Based Filtering Algorithms help in upgrading the quality of the online course materials by assessing student data to predict the student performance within the courses.
Key Words: MOOC, Online Education, Data Mining, Recommendation system, e-Learning,

1. INTRODUCTION

Nowadays education has moved quickly towards the technical world and keep in pace with. It is full of competition that would be bringing in total revolution. The leading teaching-learning handle is being the show issues in our society. Schoolbag, homework, and dull examinations are a burden of our understudy, so it must before long discover a diverse stage. In current situations, Electronic apparatuses have been utilized within the e-learning strategy which enables learners to hunt for data anyplace and anytime on the web search engine. It permits fast get to understudies to recover specific data. Many free search engine like Google, Yahoo, etc. returns the top best documents of the requirement of a student. However, the relevancy of the required documents is based on the keywords used in the query. But many new learners often struggling to find out the right keywords and the most relevant links in new learning topics [3],[4],[5]. In addition, commercial based search engines frequently

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
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place advertisement with sponsored as CPM (Cost per thousand watchers), CTR (Click-through rates), CPC (Cost per snap), or CPA (Cost per activity) over significant things which additionally distract students from picking the correct sources of content from the returned query items [3], [7], [14]. In fact, the existing research study considers only a few results (less than 20) returned by search engines [8]. Coincidentally, this grounds a few students with troubles in looking for a substance that matches their necessities. This is assessed based on the relevancy of web pages to specific inquiries but in reality, it does not represent the overall requirement of the user. Depending on the user requirements, the different set of information may be required for the same query. Hence, the queries should be considered with a profile of the user. In an educational environment where the student has different backgrounds and behavior in learning, is important in the influence of their learning advancement and acceptability. For example, a lecture video, which has prepared for an advanced level of the student, is not suitable for other levels because of uniqueness in the level of comprehension among them. It always not satisfaction [17] the relevant requirement of the students so, a perfect result could be derived from the requirement of the students based on the evaluation of their personal require result links and quarries. Similarly, an assessment gathered from a group of similar learner's profile from a group learning environment gives more significant input for the students rather than just the relevancy of the web pages. The main objectives of this study is to present an adaptive method of learning for e-learner with different capabilities when using popular web search engines. To attain this, a recommender web search system was developed to attain this; a Web search recommender framework was created as a gateway between the Google web search and the institutional e-learning gateway in order to empower the internet searcher to convey personalised search results as suggestions for learner dependent on their individual needs.

2. LITERATURE REVIEW

In recent years, most of the educational applications offer similar tools for learning to all students. So as to develop customized educational materials for an individual student, after investigating their profiles, specialists have strived to think of various recommendation systems or adaptive learning mechanisms. [1],[10]-[17]. Researcher [18] concluded that 80% of the students use and prefer web as an educational tool. In any case, not many investigations conducted on how the famous web search can be used to use students by giving them personalized e-Learning materials.Google has developed a specialized search tool, which has help for teachers to find their learning objects[3] very easily. Many well known such as Google, Yahoo, etc., search engines returned result along with the advertisement. It doesn't show any extra information with respect to personalized recommendations. [3], [19].

3. The Proposed Recommendation System:

The aim of our proposed recommendation system is to recommend to the learners based on their personalized group-based system. It acts as a gateway between the Google search engine and the organization's domain. The proposed online process demonstrates in the following Fig.3.12. When the user login, this system will automatically identify the user by the Student Information System (SIS). If the student raise query, it looks both Google search and the local server of the system. Google returns required links as usual but in the proposed system it also returns links which are personalized based on

ISSN:1624-1940
DOI 10.6084/m9.figshare.2632574
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a profile of the students.

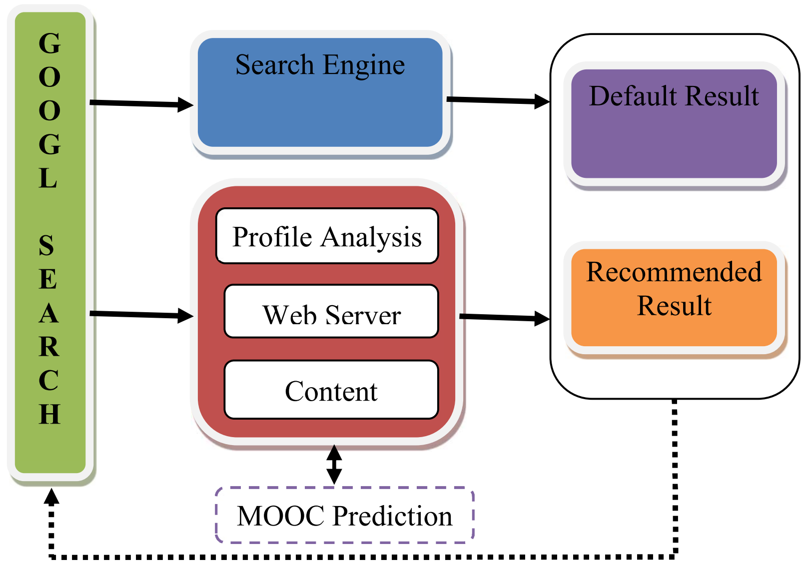

Fig.3.12 Online Processing

4. Analyzing Students' Profile:

This process aims to build and maintain individual student's profile. It enables the system to understand the distinctive learning needs and capabilities of individual students. Then it utilizes this data to improve the relevancy of returned search results by choosing the most relevant personalised links. This is accomplished by organizing the links according to each profile. To achieve this, the process has two functional elements: Analyser of Academic Record and Analyser of Behavioural Activity. Student's profile is the major element of any e-Learning system whereas this research has considered the most well-known profiling model for the user in IEEE PAPI standard [23] for modelling the analyzing the student profile. Hence, this model gets more advanced using the student profile model as a pattern which includes the following components: 1. Academic record 2. Behavioural record and 3. Contextual record. If there is any modification observed in these records, the system will be updated the data automatically for a time span which is not a few session or in a few days but it may cross a month of data as contextual data commence for corresponding to the requirement of dynamic profile.

1. Academic record and its analysis:

The past and the present academic performance of the individual student is measure by using this record. However, the records of the student's performance are derived from SIS whereas this record contains T-score of the individual student profile. This score obtained from the academic record of each student by grading policies. This score helps to classify the student's profile. We define this score as Knowledge Marks (KM) of a student.

2. Behaviour record and its analysis:

This process is responsible for continues monitoring of student profile and capturing the

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ISSN:1624-1940
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behaviour of their learning which is accomplished through their web search activity. Learning activities of every student are stored which has extracted from their session logs and the history of their browsing. These activities help to classify the level of student's interest in their suitable learning materials. It can be interpreted within a fuzzy setting. Fuzzy rules are generated by applying the decision tree. These rules permit to classify the learning behaviours of the students as Low, Low Medium, Medium and High whereas this can be done based on student behaviour pattern for representing the level of student interest based on the learning.

3. Classification of Student Profile:

The previous sections deal with interest and knowledge marks, which require further processing, of the students. Occurring to these outputs, a student's profile is classified as academic performance (KM) and behaviour of learning (level of learning interest). To accomplish this process extended classification rules are applied [5], [4], [21]. From this data, a decision tree model is constructed using the C4.5 algorithm[7] which helps to classify the student further into three groups as Beginner, Intermediate and Advance as given below in Figure 3. C4.5 is one of the top 10 Data Mining Algorithms. In this research study, the decision tree is made to translate into subsequent rules using the student's KM and their interest level.

1. If KM > 80 then assigned as an Advanced Class
2. If KM <60 then assigned as a Beginner Class
3. If KM <80 & >60 then further classified as Low (Beginner), Low Medium (Intermediate), Medium (Intermediate) & High class (Advance) based on the interest level of students.

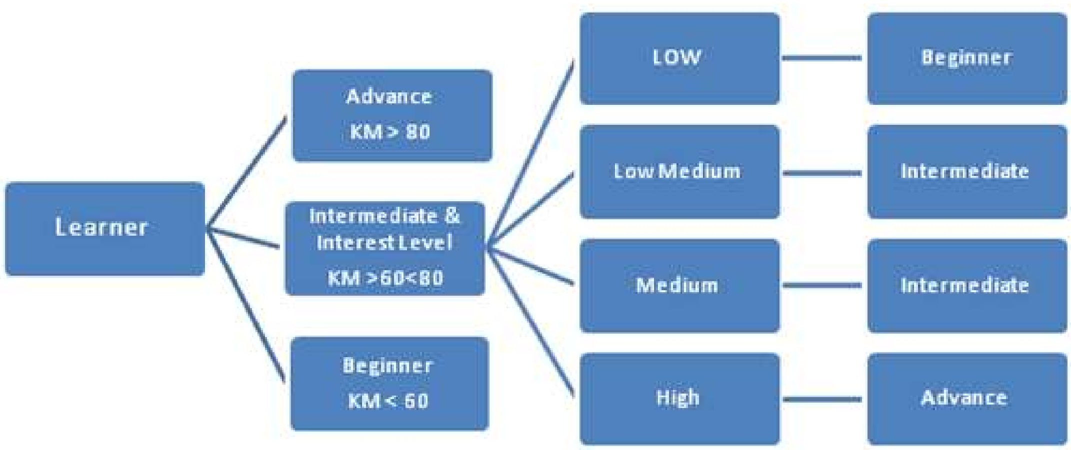

Figure 3. Student profile classification decision tree

Enhanced Re-ranking Techniques:

The proposal of a novel algorithm in this research is to manipulate and determine the rank of the link URL page based on the query search of the students using content-based RS whereas the student searched link page is the content of each student profile. According to this concept of enhancement in Re-Ranking, the architecture of this algorithm follow the fundamental concept of content-based

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filtering. This architecture has illustrated about the mode of learning from the student associated with the predictive course in the course provider whereas there are two different users available in this online predictive tool namely admin user and student users. The admin user can able to unload the datasets in the database which consists of student details and course prediction. Similarly, students user in the online MOOC course prediction has used search query for learning the topic in the online whereas the link available from the course provider for the relevant topic to learn with various mode of learning. The student used a keyword for a searching keyword to categorize the student based on their learning behaviour. The student profile classification is based on the modification of KM and interest level whereas this re-ranking algorithm has focused on the level of interest. The interest score is accomplished using this level of interest and URL page searched by the student. However, this is done through each student to understand the mode of learning from the course provider and also analyze the student capability of learning. In other hands, academic record analyzer help to analyze the KP of the student using T-score and the average of T-score is stored in the dataset which gets uploaded through admin. This architecture of re-ranking has proposed to analyze the mode of learning from the student through online and student's capability of learning, language skills, and another expressive context. The proposal of enhanced Re-Ranking algorithm has been implemented for the Re-Rank of links which are viewed from the student in order to study their relevant topics in the online. The procedure of Re-Ranking is listed below steps.

1. The available links in the database based on the student searched link page for studying their relevant topics.
2. The searched link pages are made to be sorted based on the student used and ranked accordingly which is send as a final output searched pages.
3. The final output searched pages count is sending to enhanced Re-Ranking algorithm for processing Re-Ranking the link based on the number of student searching the similar link pages.
4. This Re-Ranked link is sent as a final output student searched link page count which is made to be looped to update the ranking frequency.

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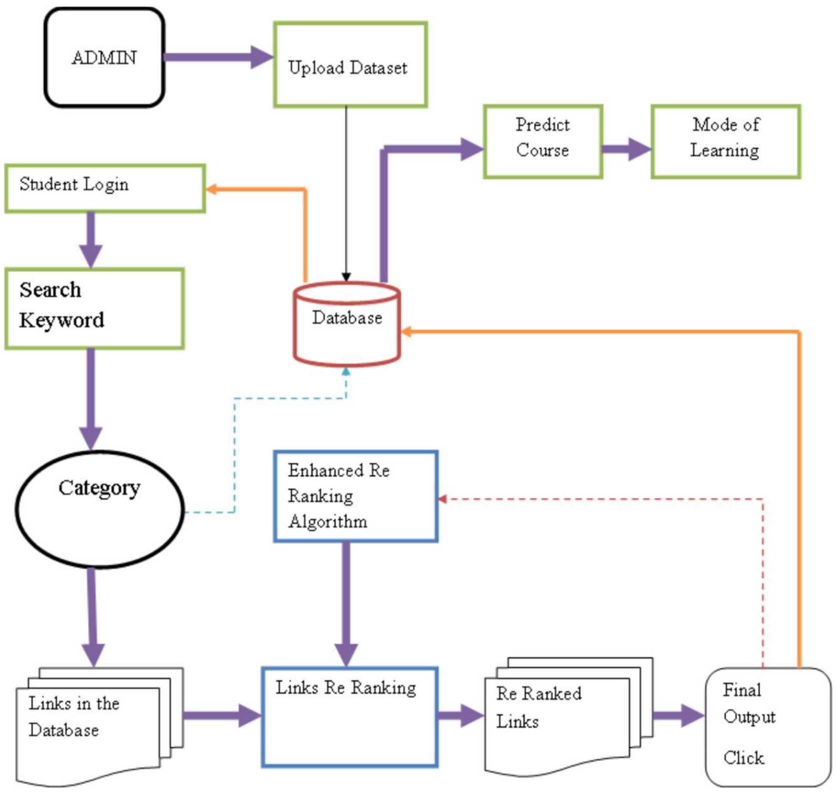

Figure 3.15 Schematic of Enhanced Re-Ranking Architecture

Re-Ranking Algorithm is achieved by taking the actual rank of the page then calculates the Current Rank of the link.

Final Rank of the Link(Cr)=Click Value(Cr)+Actual Rank(Lr)

Enhanced Re-Ranking Algorithm:

```
Enhanced Re-Ranking Module()
{
For Each Links in L,
{
Rank=Actual Rank;
Final Rank= Click Value(Cr)+Actual Rank(Lr);
Result= Rank+Final Rank;
}
Sort out the Document in L by Result;
Return L to the search Engine;
}
```

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5. Evaluation method of student profile Analyser:

To appraise the ease of use, usefulness, and effectiveness of the proposed personalized Web search recommendation system, experimentation was designed and conducted on the undergraduate students of our university. Google API has utilized for integrating the Google search engine in a prototype whereas the major purpose of this experiments is made to be prototype available to the participants for accessing the system using the creation of individual accounts. In total, there are 80 students have participated in this experiment whereas the pre-graduate students and the respective standard faculties of computer science have chosen as participants for this research. The intention of working with computer science students was derived from the assumption that they were more technically sound than others in using a search engine. The academic record analyzer is used to determine the T-score of the academic topic as TI, T2 and T3 using Knowledge Mark(KM) which aided for analyzing the T-score as produce the result as the status of beginner and Advance learner. According to the T-score students are made to be categorized as an advance learner, intermediate and beginner.

The behaviour activity analyzer is used to determine the student's interest level with their login count, link click count and count of the page clicked for search. These counts of search are aided for a category the mode of learning from the course provider link. This click count will Re-rank the web link using the algorithm of enhanced Re-Ranking whereas the student profile analyzer has considered both details of academic analyzer and behaviour analyzer to store the details in the database. The course prediction with the mode of learning can be viewed and admin user likes teacher and staff. The prediction of student capability of learning and topic along with status shows their talent in understanding the subject even in the digital strategy. The behaviour analysis is done through the No. of login, No. of search per page and No. of click. The student namely Mark Bonnell, Rose Neville Lavinia Beaudoin have the maximum no. of click as 99 which lies in the mode of learning as virtual reality. However, all the three students have done the similar no. of search and no. of login.

Performance Analysis on Digital Strategy

In order to recall the content in the web with enormous and dissimilarity has prompted the requirement for the frequent concept in one search results that suitable for all users recommendation in the recent web search engine. According to this proposal, this is an impulse and vital study is the student who is a recommendation to appropriate material of E-learning from the web which required to be considered. In order to meet the need of the student, designed and developed of digital strategy have introduced in accordance of fuzzy rule classification and content-based filter with RS as Re-Ranking based system to the users of web search engine. This query search has focused on distributing an important personalized query search resulted in a recommendation which mapped the other individual students profile of search history. Therefore, adequacy and consistency of proposed technique can able to measure the student's capability of studying and mode of learning by conducting two kinds of group testing with the pre-graduate students of the school and the respective teacher of computer science.

In this research, data mining technique used for an online course studied for 80 pre-graduate

ISSN:1624-1940
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students whereas fuzzy rule and content-based filter with RS as enhanced Re-Ranking algorithm is utilized in the online MOOC course prediction for searching the query by a query search engine in this web site. The link of the searched query is available in the respective student's history and searched link URL pages which are searched from a student using keyword in the query search for the related topic can be viewed. This study assists for calibrating the student's capability and mode of learning with respect to the course provider namely virtual reality, video conferencing, chatting, email and questions. The link searched is made to be scored and ranked. This proposed technique help to generate the top K link according to the student searched query which is available in the online MOOC course prediction. Based on the graph page, the graph for course, mode of learning and student profile can be viewed is shown in Figure 4.7. These graphs have illustrated the mode of learning, topic studies from the students are analyzed in order to observe the capability of a student in learning through digital strategy.

The student studied from the subject of computer science with various topics namely C, C++, Java, Dotnet and Python whereas these kinds of topics are learned with various mode of learning from several course providers. The choosing of the topic has illustrated the student knowledge point in the subject and interest levels. Figure 4.7 has shown about the student interest in topics and their status. However, most of the students are preferred to study python which is 92 followed by Java as 42 students and the beginner students with 12 numbers are preferred to study C++.

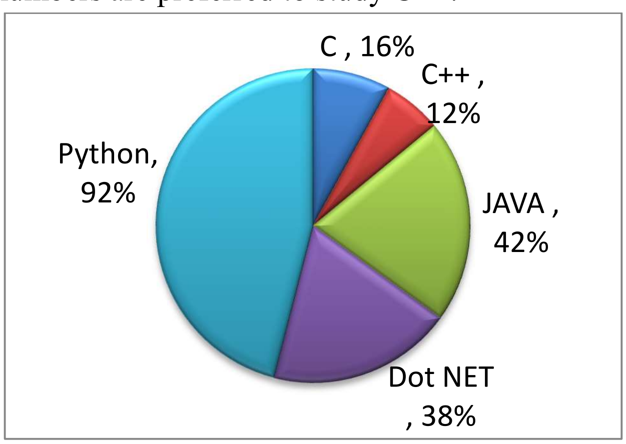

Figure 4.7 Graph for course in graph page

The way of learning has chosen from the student's in the online MOOC course prediction is virtual reality, video conferencing, chatting, Emails and Questions whereas most of the student have studied their course from the course providers are virtual reality due to its ease of study and simple way to observe the topic quickly and worked out with various examples. In figure 4.8 has shown that followed by virtual reality, video conferencing play a role with tutor interaction of study with the relevant topics.

ISSN:1624-1940
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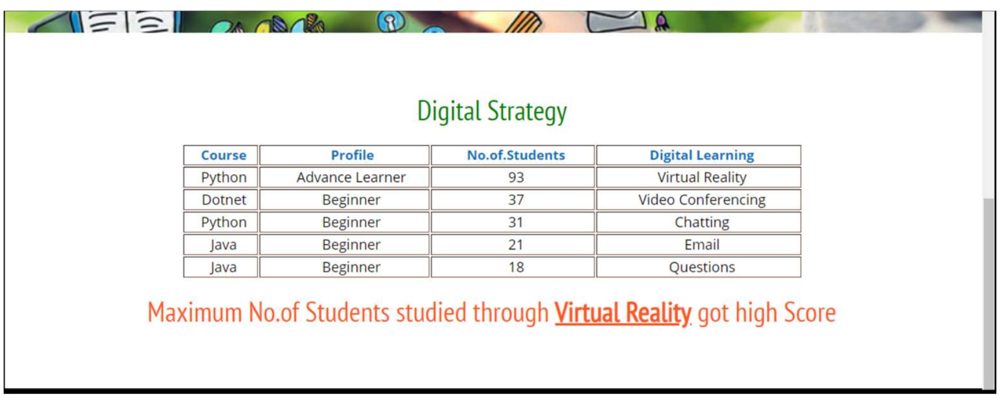
Figure 4.8 The way of learning in graph page

Performance result of online MOOC course prediction

The result with the performance of online MOOC course prediction has illustrated the digital strategy with online learning from the students is shown in Figure 4.12. This strategy explains the mode of learning from the student through online for the course whereas the status is named with profile as Beginner and advance learner. There is a maximum number of student studied with the virtual reality as a mode of learning whereas the course python consists of 93 students studied in the mode of virtual reality.


Digital Strategy

Course	Profile	No.of.Students	Digital Learning
Python	Advance Learner	93	Virtual Reality
Dotnet	Beginner	37	Video Conferencing
Python	Beginner	31	Chatting
Java	Beginner	21	Email
Java	Beginner	18	Questions

Maximum No.of Students studied through Virtual Reality got high Score

Figure 4.12 Digital strategy of student based on course

In this online MOOC course prediction, the student who got a high score in the various course is illustrated in Figure 4.13. The advance learner profiles based on courses to the student count is described whereas 65 students studying the course python which is the most student learned the

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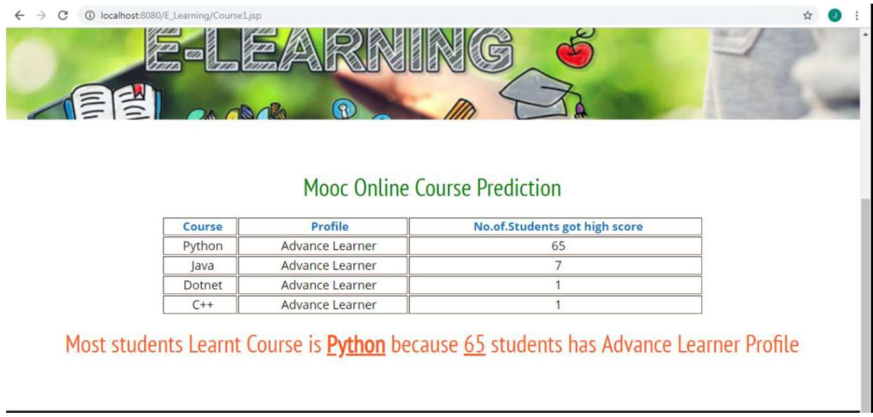

course.

Figure 4.13 Student count in Advance Learner based on course

Evaluation of proposed Enhanced Re-Ranking Technique

In order to evaluate the performance of Re-Ranking algorithm with RS, the performance metrics of information retrieval are utilized for evaluating these search engines. Moreover, these metrics are broadly utilized over the scenario of information retrieving and applied for domain nearly search engine that recovery a few sets of best results to questions several probable results. The online experiment can achieve the most real testing results among the three evaluation methods. The advantages of an online experiment are that the entire performance of the RS can be evaluated, such as long-term business profit and users‘ retention, rather than some single metrics. Therefore, an online experiment can be used to understand the impact of the evaluation metrics (Prediction, Recall, and F-Measure) on the overall performance of the system. The balance of these metrics will be considered when choosing the parameters of the recommendation algorithms. In many real recommendation applications, the designers of the system wish to influence the behaviors of users using recommender systems. Therefore, when users interact with recommender systems based on different algorithms, the designer wishes to evaluate the influence of the recommender systems on users‘ behaviours through online experiments.

Recall is defined as the number of items recommended search divided by the total number of relevant documents.

$$Recall = \frac{Items\ recommended}{All\ items} = \frac{True\ Positive}{True\ Positive + False\ Negative}$$

The recall is defined as the number of items recommended search divided by the total number of relevant documents.Precision is defined as the number of items recommended search divided by the total number of recommendation by the search..

$$Precision = \frac{Items\ recommended}{All\ Recommendation} = \frac{True\ Positive}{True\ Positive + False\ Positive}$$

F-Measure is a harmonic mean of recall and precision which compromise between the precision and the recall.

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$$F - Measure = \frac{2 * Precision * Recall}{Precision + Recall}$$

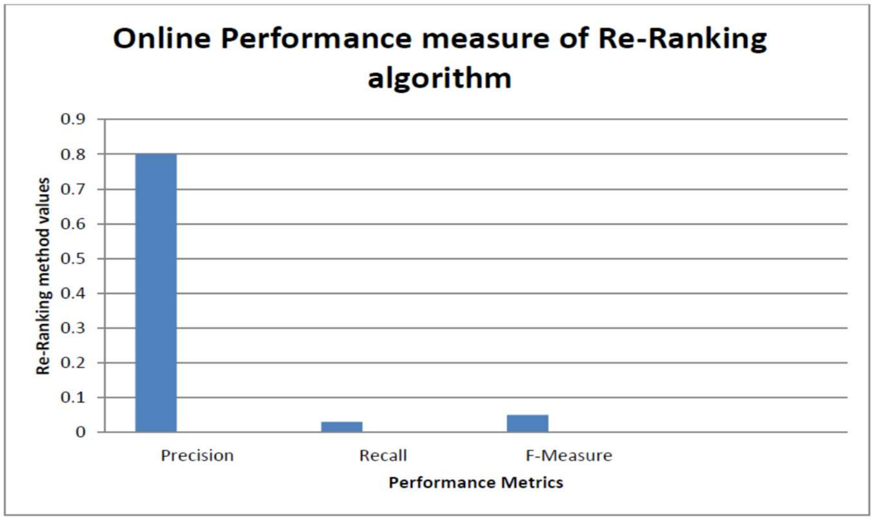

Figure 4.14 Performance metric evaluations for Re-Ranking algorithm in RS

5. Conclusion:

The online MOOC course prediction is utilized to improve the student learning behavior through online E-learning has developed the skills of language, listening, writing and speaking through the interaction of online course provider based on the mode of learning like virtual reality, video conferencing, chatting, Email and questions. This kind of learning has improved the skill of learning which can be analyzed using T-score and interest level of learning from the students. The mechanism of content-based filtering with RS in the approach of Re-Ranking has helped for searching the query easily which have the ability to retrieve the efficient link for the student search which learned previously. This proposal of Re-Ranking have improved the students learning behaviour by searching the keyword effectively using query search through re-ranked links which tend to retrieve the top K links to attain the better status of students based on the course and students who studied their related topics in the online through online MOOC course prediction have improved their learning capability, language skills and creativity with virtual reality mode of learning. Most of the student's profile has improved as advance learner due to virtual reality learning provided from the top prior course provider links which can be obtained through Re-Ranking.

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