INTERNATIONAL JOURNAL OF ADVANCE RESEARCH, IDEAS AND INNOVATIONS IN TECHNOLOGY

ISSN: 2454-132X
Impact factor: 6.078
(Volume 6, Issue 2)
Available online at: www.ijariit.com

Recommendation system of course selection

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ABSTRACT

This module is a program for recommending various courses on the basis of academic results and student selection. Students choose specific courses of study because of their interests and possible future development upon graduation. It is a unique approach to student counselling that proposes different approaches to learners and resources, processing natural languages, indicators for developing skills and knowledge. It collects course information and commends them according to their students' preferences, interests and needs. Choosing the wrong subjects means the discrepancy between the student's understanding, power and personal interest. Problems arise when a student is not interested in the course that is not well matched with the student's ability. In this module, the system assesses the power of psychometric tests and is based on their previous learning outcomes. Incorporating all aspects, speaking and deciding which lessons should be recommended by learners. So it's nice to have some kind of smart complimentary tools that need to be made to help them.

Keywords— *Recommendation system, Course selection, Psychometric test, Academic results, Market trends*

1. INTRODUCTION

The Recommendation Program is an app that is able to present the user with an item suggestion, available on the basis of his or her previous preferences and social preferences and preferences. Complimentary Plans help us to reduce the overload of information we receive these days, providing, at the same time, customized access to information for a specific domain. Recommendation programs are used in areas such as ecommerce, entertainment or digital libraries to address the vast amount of information they produce. However, there are many other fields that present the same problem, such as those domains related to education and learning.

Suppose, in a teaching environment, a student finds himself exposed to a host of learning materials, such as practices or exams. The student has more of his own resources than he is able to use, and he has no idea where to start, so bearing in mind that learning materials are categorized, he decides to start with the basic level. The student looks through all of these teaching materials on their topic and remembers his friend telling him how much he liked those reading material related to a particular topic. The student decides to start with those things, and when he is done with them, he calls his friend to congratulate him even more as those who have passed have done exactly what they wanted. If we move this process into the field of learning, how can a student find his or her favourite subjects? To solve the problem of overload problem different strategies can be used, and one of them is based on Recommendation programs.

2. PURPOSE

Today there are many courses available for students, and sometimes it is difficult for a student to find information related to those subjects and decide which subject to take. This work aims to create a program to promote online courses for users based on their profile and similarity with other users. Therefore, users will not feel tired while seeing details of their interests and will end up getting involved and interested in using the system.

3. BACKGROUND

The compliment program is a truly revolutionary way to provide education in the future of life, in comparison with the general facial education teaching and learning. Today more and more people have benefited from many regeneration programs. However, high diversity students on the net have new challenges in the "one-size-fits-all" learning model, where one learning set is offered to all or some of the students. In fact, students may have many interests; even sharing common interests, they will have different levels of experience, and thus cannot be treated in the same ways. It is very important to provide a customized program that may be mentally tailored to the interests and levels of students.

Recommendation systems are installed on industrial and non-profit websites to predict user preferences. Most advisory functions include analyzing users' information and providing useful information for any prediction. The recommendation system may be a piece of computer code that helps users identify interesting and relevant first-hand reading material from an additional material range. Recommendation programs can also be supported by collaborative filtering (at user ratings), content-based filtering (by keywords), and hybrid filtering (per content-based filtering).

4. EXISTING PROGRAM

Recently, many aspects of getting a college education have changed. The amount of lesson-related information available to students is increasing rapidly. This wealth of information created the need to help students discover, organize and use resources that are relevant to their goals, interests and current knowledge. One of the concerns is that students do not have to decide which courses to take.

Of particular concern is the graduating students who have more freedom to choose their studies while being more concerned with taking courses that influence their progress towards career goals. To make these decisions, they use information from academic catalogs and schedules, consult with their advisors and seek guidance from their classmates, especially those with similar interests. To provide better decision-making support for students who wish to make appropriate academic decisions, we have developed a scholarship program that recommends courses to students based on other similar students.

5. MODULES

5.1 Natural Language Processing

Natural Language Processing (NLP) is about developing programs and services that are able to understand human languages. Some practical examples of NLP speech recognition e.g.: google voice search, understanding what content is about or analyzing emotions etc.

5.1.1 Benefits of NLP: As you all know, there are millions of gigabytes daily produced by blogs, social websites, and web pages. There are many companies that collect all this information of their discerning users and their wishes and provide these reports to companies to change their plans. Suppose a person likes to travel and often looks for a place to go during the holidays, user-generated searches are used to provide ads related to online hotel and flight booking apps. Search engines aren't the only natural language processing function (NLP) and there are a lot of surprises
for use there.

5.1.2 Use of NLP

- Here are some of the most effective uses of Natural Language Processing (NLP):
- Search engines like Google, Yahoo, etc. Google's search engine understands that you're a tech tech and shows you results related to you.
- Social websites eat like Facebook news feeds. News feed algorithm understands your interests using natural language processing and shows Ads related to posts more than any other posts.
- Speech engines like Apple Siri.
- Spam filters such as Google spam filters. It's not just about regular spam filters, now
- spam filters understand the contents of the email content and determine whether it is spam.

5.2 Naive Bayes subdivision

The relationship between attribute set and class variable is not apparent. Regardless of whether the characteristics are same, the class mark may contrast in preparing set even and thus cannot be anticipated with conviction.

Reason: loud information, certain different properties are excluded from the information.

Bayesian Classification

• Problem articulation:
– Given highlights X1,X2,… ,Xn
– Predict a name Y

Bayes Classifier

A probabilistic structure for taking care of characterization issues

Contingent Probability:

$$P(C|A) = P(A, C)/P(A)$$

Bayes Formula:

$$P(C|A) = (P(A|C)P(C))/P(A)$$

5.3 Bayesian Classifiers

$$P(C \mid A_1 A_2 \ldots A_n) = \frac{P(A_1 A_2 \ldots A_n \mid C)P(C)}{P(A_1 A_2 \ldots A_n)}$$

Approach:
– register the back likelihood P(C | A1, A2, … , A) for all estimations of C utilizing the Bayes hypothesis
– Choose estimation of C that maximizes P(C | A1, A2, … , An)
– Equivalent to picking estimation of C that maximizes P(A1, A2, … , An|C) P(C)

• How to gauge P(A1, A2, … , A | C)?
Innocent Bayes Classifier

Accept freedom among qualities Ai when class is given:
– P(A1, A2, … , A |C) = P(A1| Cj) P(A2| Cj)… P(An| Cj)
– Can evaluate P(Ai| Cj) for all Ai and Cj.
– New point is arranged to Cj if P(Cj) Pi P(Ai| Cj) is most extreme.

Hearty to segregated clamour focuses
Handle missing qualities by disregarding the example during likelihood gauge estimations
Hearty to superfluous properties
Autonomy suspicion may not hold for certain properties

$$P(Y|X_1, \ldots, X_n) = \frac{\overbrace{P(X_1, \ldots, X_n|Y)}^{\text{Likelihood}}\overbrace{P(Y)}^{\text{Prior}}}{\underbrace{P(X_1, \ldots, X_n)}_{\text{Normalization Constant}}}$$

Model Parameters
The issue with unequivocally displaying P(X1,… ,Xn|Y) is that there are generally such a large number of parameters:
– We'll come up short on space
– We'll use up all available time
– And we'll require huge amounts of preparing information (which is normally not accessible)

5.4 Naive Bayes Training
• Training in Naïve Bayes is simple:
– Estimate P(Y=v) as the portion of records with Y=v

$$P(Y = v) = \frac{Count(Y = v)}{\#\ records}$$

– Estimate P(Xi=u|Y=v) as the portion of records with Y=v for which Xi=u

$$P(X_i = u|Y = v) = \frac{Count(X_i = u \wedge Y = v)}{Count(Y = v)}$$

Practically speaking, a portion of these checks can be zero
Fix this by including "virtual" checks:

$$P(X_i = u|Y = v) = \frac{Count(X_i = u \wedge Y = v) + 1}{Count(Y = v) + 2}$$

– This is called Smoothing

Naïve Bayes is:
– Really simple to actualize and regularly functions admirably
– Often a decent first thing to attempt
– Commonly utilized as a "punching pack" for more brilliant calculations

6. APPLICATIONS

(a) Encouraging the coordination of data from blended sources
(b) Dissolving ambiguities in corporate phrasing
(c) Improving data recovery accordingly lessening data over-burden and expanding the refinement and accuracy of the information recovered.
(d) Distinguishing significant data as for a given area.
(e) Giving dynamic help

7. DESIGN

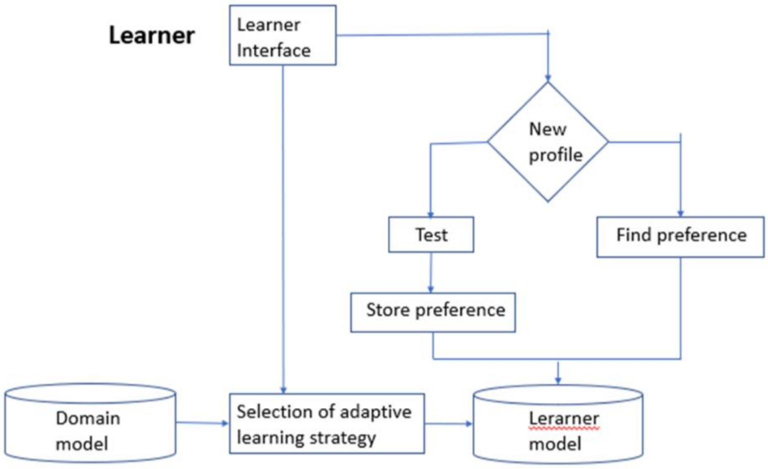

Fig. 1: Process of selecting adaptive learning

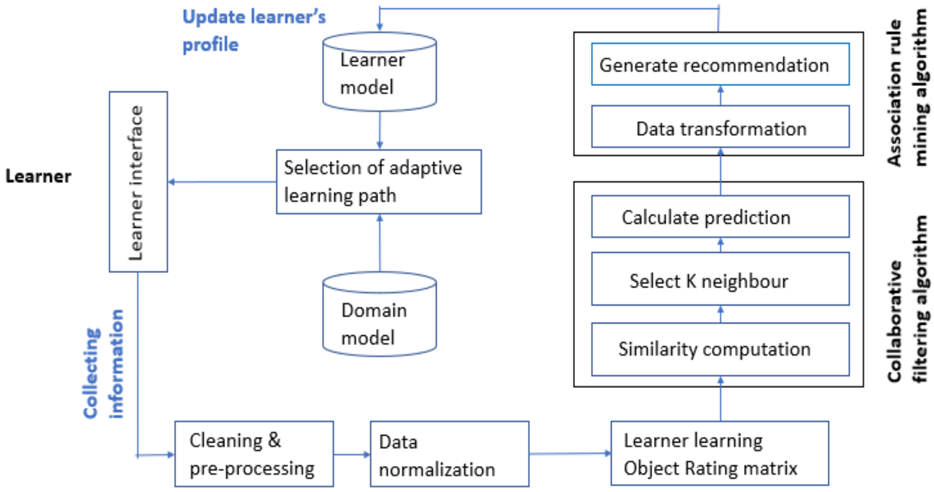

Fig. 2: Recommendation Process

8. ACKNOWLEDGMENT

We have taken efforts in this project. However, it would not have been possible without the kind support and help of many individuals. We would like to extend my sincere thanks to all of them. We are highly indebted to Swati Patil ma'am and Suvarna Pawar ma'am for their guidance and constant supervision as well as for providing necessary information regarding the project & also for their support. Our thanks and appreciations also go to all those people who have willingly helped us out with their abilities.

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