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System Oriented Social Scrutinizer: Centered Upon Mutual Profile Erudition

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Abstract— Social recommender systems are getting up more attention for product advertisement and social connectivity. A good recommender
should think about the system and the user. The user will have a preference list of some items and these preferences can be useful in suggesting the things which can help the endorsing system to identify better items. In this paper, the idea of social recommender systems as a pattern matching and regular expression making is used for unification of similarities. The concept of mutual profile pattern expression can be applied on various networking platforms. In these type of shared platforms, people all around the globe share resources and interact with each other. In order to manage or scrutinize users according to their interests and likeness, the mutual profile pattern of users can be used. Further predicting of membership function is performed to show how much extent does the profile matches.

KEYWORDS- DFA, Transition Table, Regular Expression, Pattern Matching, Probability, Membership Function, Fuzzification

I. INTRODUCTION

With the use of the Internet, there have been a lot of people who are interested in doing research on the most popular topics that they would like to learn about. So, they can easily find what they need to know to complete the task. But sometimes it becomes difficult to find relevant information or connections in social platforms. Search engines are better known for these type of task but difficult to use. So here comes the role of scrutinizer in social platforms. Scrutinizer has become vital for decisions making about information on the web. However, they are facing several challenges, including the need for adequate training for users, the absence of effective standard protocols for how recommendation systems should be used [1] [10] [17].

Social networks have grown remarkably as of late. The endless supply of data produced by using sites for social networking, which may be able to alleviate some of the problems associated with RS. There are many different social networking websites, including ones for social tagging, social bookmarking, and sharing photographs and videos [5] [53] [81]. Social interactions can be leveraged to achieve better results even while traditional RS does not. You may use ratings and social connections to figure out where missing values are. The incision of social networks into RS, yield a novel system known as the Social Recommender System is created (SRS). This algorithm uses useful data from social networking sites to hunt for intriguing patterns. Regarding its features for creating useful suggestions, SRS is gaining a lot of interest [22]. Considering this interest, to our knowledge, academics have not yet thoroughly examined all of SRS's properties. This document clarifies a number of SRS characteristics [8] [67] [82].For scrutinizer generation role of automata theory is vital. Automata theory is a field of computer science that deals with the design of abstract self-propelled computing devices that automatically perform a given set of operations. A machine with a limited number of conditions is called a finite machine. A finite state machine is a mathematical model of computation. Only one condition on this machine can be active at that time. This means that the machine needs to move from one state to another in order to perform various actions. This is a mathematical tool used to describe processes that include inputs and outputs. In addition, it is suitable for building different types of software, such as systems that check the accuracy of circuits and protocols, and lexical analysis components of compilers. Finite-state machines have a finite set of conditions that accept or reject strings. Managing or scrutinizing two similar entities can be done with finite state machines using mutual pattern matching. The patterns of entities can be generated depending on various scenarios and environment. These unique patterns might contain some similar dataset properties which will help in analyzing these entities in their similarities and uniqueness [12] [26] [33].

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This work is divided into six portions. Section 1 gives outline and previous works about scrutinizer or recommendation systems. Sections 2 elaborate the concept of Mutual Profile Pattern (MPP). Section 3 describes the evaluation process for MPP. Section 4 presents method of refined solution with fuzzification. Section 5 gives applications followed by conclusion and future work in Section 6.

II. PREVIOUS WORK

A recommender system can be considered as a person who finds and recommends items to other people. An example of an RS would be an Amazon seller that uses a recommender algorithm to recommend products that will be most likely to satisfy the preferences of his/ her customer [1] [9] [25]. The collaborative filtering technique aims at identifying users who are more similar to the items than to other users. More specifically, the CF method identifies users who have a similar set of items. Memory-aware and learning-aware methods can make better predictions with less data. But the performance of the models obtained depends on how the data is used [2] [27].

Content based filtering based upon archival or past activity. The most significant advantage of CBFs is that they are based on explicit user feedback, which is not only time-consuming but also expensive. However, even though the user's feedback is time consuming, it can lead to much better recommendations than the ones. It is possible that a user may have a good phone connection and is able to see the recommendations. Yet, this may be misleading if there are too many or too few recommendations for a given phone. In this case, the system may perform negatively [3] [39].

In order to be competitive, hybrid-CBF algorithms should use a small and carefully selected set of features, which are chosen to maximize the benefits and avoid any negative consequences. As a result, a hybrid CBFN-CFN approach is typically constructed. It is not favorable as for instance, a person who is knowledgeable about programming will know that a good balance of static and dynamic programming techniques can be used to solve a problem that can't be solved by only one of these techniques [4] [42].

Graph mining can also find items where similar ratings exist. Graph mining is a data mining technique that is widely used in many industries. However, the techniques are mostly used for web sites and blogs where it is easier. There are several methods for adding nodes to the node set. One approach is to insert the edges between the new nodes, which is called the Edge Builder method. Due to storage and cost operations this method is used with combinations with other methods [5] [43] [58].

Table 1: Previous Studies

S No.	Paper Title	Year	Approach	Advantages	Disadvantages
1.	Collaborative filtering recommender systems [2]	2011	Collaborative filtering	Random and varied recommendations, no cold-start issue with an item, and no subject knowledge necessary	Information sparsity, the dark sheep issue, peddling assaults, adaptability, and quality in light of appraisals are among the issues that affect users.
2.	A general chart based model for proposal in occasion based informal organizations [16]	2015	Graph	Simple to locate related users and items	Ranking of outcomes and graph modeling
3.	Research-paper recommender frameworks: a writing study [11]	2016	Content filtering	Independent of the user, transparent, fresh suggestions, and no cold-starting of items	Overspecialization, the importance of user input, and the issue of cold start users
4.	Information based proposal: a survey of philosophy based recommender frameworks for e-learning [17]	2018	Knowledge	No cold-start issue, no ratings required	Knowledge acquisition requirements and fixed suggestions
5.	A clever profound mixture recommender framework in light of auto-encoder with brain cooperative separating [13]	2018	Hybrid	Strengthens system stability and performance	Understanding of how to combine approaches for a certain domain
6.	Investigating segment data in web-based entertainment for item proposal [18]	2016	Demographic	No need for ratings, since suggestions will get better with time.	Issues with new users, inaccurate data, a lack of demographic information, and privacy

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Knowledge based systems provide insight into the future behaviors of the users who have rated the items such as the most likely next action for a user who has rated a product X. There is one piece of information that they provide by naming that. The domain-specific knowledge is built from user requirements, and user input is collected from the dialog flow. The dialog user has to be familiar with system-provided knowledge to successfully complete the system. To make the process easier, a system that can integrate this knowledge is required which is hard to master at [6] [59] [68].

(Refer to Figure 1) Recommender Systems are collaborative, query-free agents with the goal of recommending things, events, connections, and information to others. The main goals of RS are to satisfy consumers and build enduring relationships with them. Although a static user profile is frequently used in existing RSs, it is insufficient to assess user interests and preferences. To ensure accuracy and user pleasure, RS dynamics are crucial factors. Recommendation Systems (RS) are categorized in the literature under a variety of headings, incorporating methods based on collaboration, content-based filtering, hybrid, graph, knowledge, and demography. Some of the strategies have been utilized by well-known websites like Netflix and Amazon.com for commercial purposes. Other methods of recommendation exist as well, including those based on utility, fuzzy logic, or deep learning [15] [20].

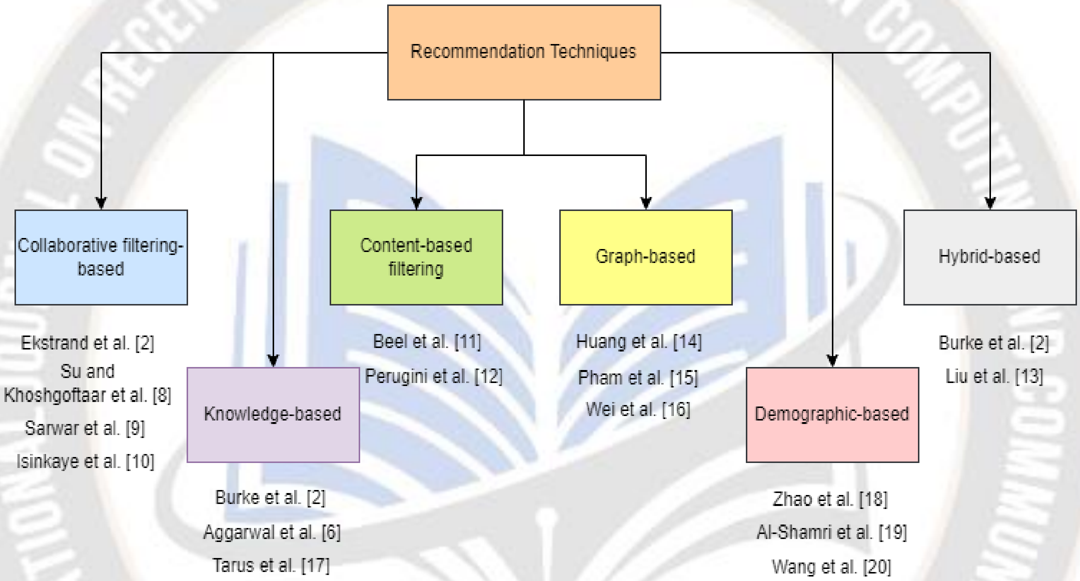

Figure 1: Recommendation Technique

(Refer to Figure 2) Many different aspects are being worked on in this domain, and different questions in diverse categories are being asked. The majority of conventional similarity between users is measured. Nevertheless, because the user-item matrix has so few ratings, CF-based techniques frequently struggle with the issue of data sparsity. Through social connections and groups, social recommenders provide more pertinent suggestions [48] [59] [77].

As a result, issues like trust, data sparsity, and cold-start concerns may be handled by SRS with ease. A variety of criteria that take into account the characteristics of SRS can be used for classification. Semantic filtering, temporal dynamics, different social relationships, temporal tags, trust, groups, and cross-social media data have been highlighted as characteristics of these systems. All of these metrics have not been categorized by any of the SRSs that have used these attributes autonomously in the literature. Although computational complexity may rise when these qualities are used to create SRSs, the recommendations that emerge may be useful and noteworthy [55] [60] [74].

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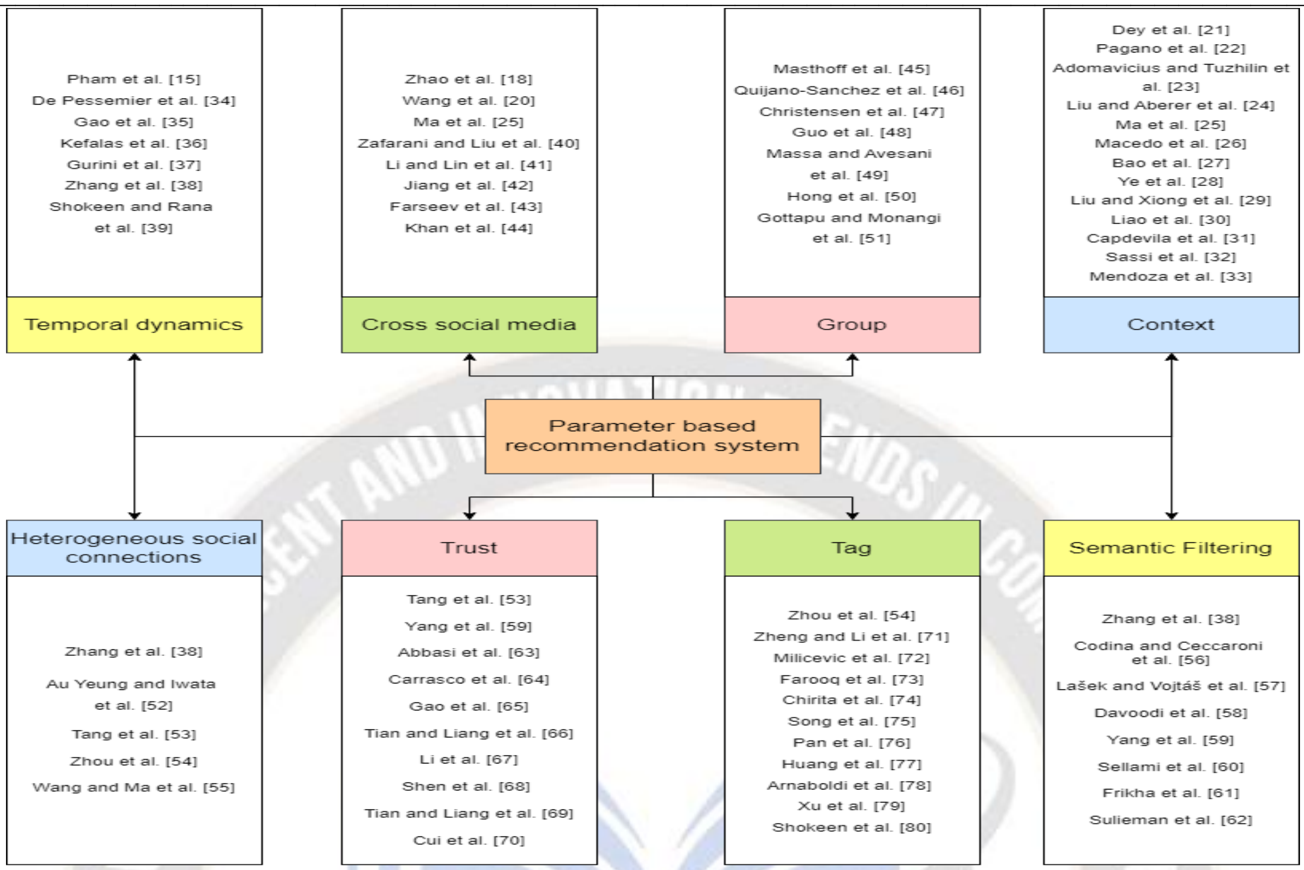

Figure 2: Parameter based recommendation system

III. MUTUL PROFILE PATTERN AS REGULAR EXRESSION

For unification of every mutual profile formation of users lets say X and Y can be formed as a pattern which can be later treated as a string. For this, prerequisite are to capture some of the specific parameters of users X and Y respectively. These parameters can be varied on the type of environment
For example consider a scenario, on basis of five parameters:

- College name (CLG)
- Branch (BR)
- Current year (YR)
- Hosteller(HOS) or day scholar (DS)
- Lateral entry(LE) or not (LEN)

Let user X parameters be:
[ABC, CSE, 2, HOS, LE]

Let user Y parameters be:
[ABC, IT, 2, HOS, LEN]

(Assumption: 0-> false, 1-> true, as described in following paragraph). The process of generating the initial pattern is shown in the following

A. The College name (CLG) of User

This is the first parameter of the user. Let's consider the user X belongs to the college 'ABC'. The other user Y belongs to the college 'ABC'. As the both parameters are same, thus increase in percentage will be added to the mutual profile pattern [7]. Representation is shown in Figure 3.

B. The Brach BR of the User

The second parameter of the user X belongs to the branch 'CSE' and the other user Y belongs to the branch 'IT'. As the both parameters value are different thus there will be a fall in percentage to the mutual profile pattern [7]. Representation is shown in Figure 4

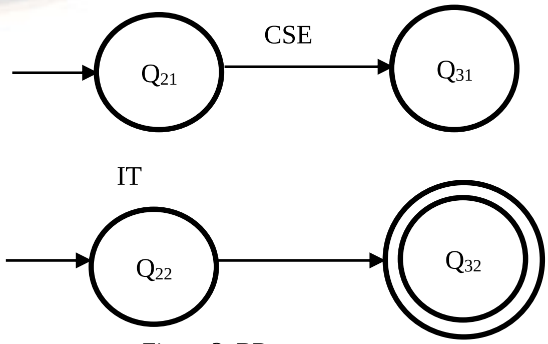

Figure 3: BR as a parameter

C. The current year (YR) in which the user is persuing:

Let's consider the user X belongs to the year ‘2’. The other user Y belongs to the year ‘2’. As the both parameters are same, thus increase in percentage will be added to the mutual profile pattern [7]. Representation is shown in Figure 5.

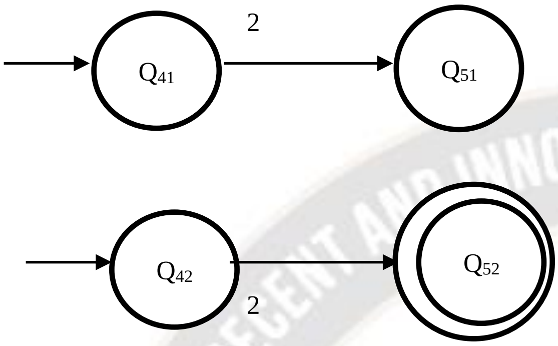

Figure 4: YR as a parameter

D. User is hosteller(HOS) or day scholar(DS):

Let’s consider both user X and Y are hosteller. As the both parameters are same, thus increase in percentage will be added to the mutual profile pattern [7]. If any of user become day scholar, then the data can be changed dynamically in future. Representation is shown in Figure 6.

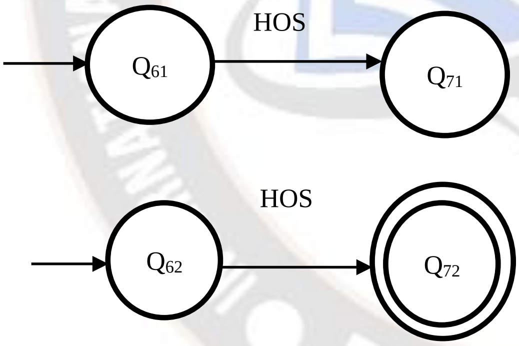

Figure 5: HOS as a parameter

E. User admitted through lateral entry(LE) ornot (LEN):

For fifth parameter, let's consider the user X admitted to the college through lateral entry. The other user Y gets admitted to college without lateral entry. This will result into fall in percentage of mutual profile pattern [7]. Representation is shown in Figure 7.

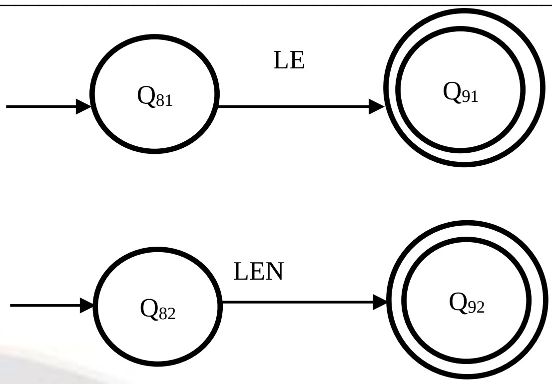

Figure 6: LE / LEN as a parameter

F. FORMATION OF REGULAR EXPRESSION

On the basis of five different parameters described earlier, pattern generation can be done which can be further used for making the regular expression.
As described earlier,
For user X parameters:
[ABC, CSE, 2, HOS, LE]

For user Y parameters:
[ABC, IT, 2, HOS, LEN]

Thus mutual profile pattern (MPP) can be formed by matching respective parameter X and Y of two users.

The assessment is carried out using higher percentages of MPP are more likely when there are more 1s, and lower percentages of MPP are more likely when there are more 0s.

X: [ABC, CSE , 2 , HOS , LE]
Y: [ABC, IT , 2 , HOS , LEN]
MPP: [1 , 0 , 1 , 1 , 0]

As for all the parameters having same or equal response, the value of MPP will be 1 and for unequal responses, it will be zero.

- As X and Y are in same college, therefore value of MPP for CLG will be 1.
- Now for BR as both X and Y branches are different, therefore MPP for BR is 0.
- In case of YR, both X and Y are persuing in same year, thus MPP for YR is 1.
- For HOS, both X and Y are hostellers, hence MPP for HOS is 1.
- For last parameter LE, both X and Y are different, thus MPP for HOS is 0.
- MPP formation is done.

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The resultant MPP has been formed and it can be re-written as in the form of a string that is '10110'. The regular expression for the newly formed string will be $(0+1)^5$. Here 5 denotes the number of parameters and it is formed over $\sum = \{0,1\}$. Thus in a similar manner string can be obtained from MPP but for generating DFA refer to figure 6, we had to treat string as a substring and concatenate (0+1) on both sides. Thus, $(0+1).(0+1)^5.(0+1)$ will be the required regular expression to be formed. Further MPP can be generated depending upon the number of parameters mutually matching to each other. Table 3 describes the transition for substring "10110".

Table 2: Transition Table of DFA having substring "10110"

S No.	***States***	***Input Symbols***	
		0	**1**
1.	→Q0	Q0	Q1
2.	Q1	Q2	Q1
3.	Q2	Q0	Q3
4.	Q3	Q2	Q4
5.	Q4	Q5	Q1
6.	Q5	Q5	Q5

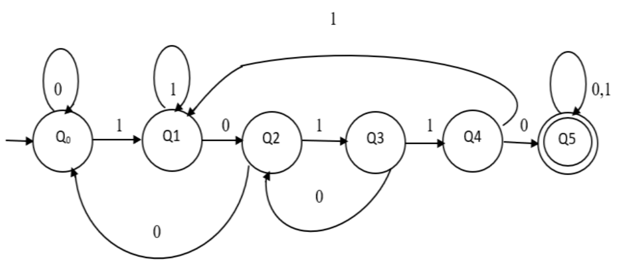

Figure 7: DFA for substring "10110"

Algorithm for the MPP generation has been described at algorithm 1 for a particular example for understanding the algorithm. The dataset shown at table 4 had been created and tested for the code illustrated earlier. Data has been collected as a set of different parameters from surrounding students who studied in various colleges. Then MPP is generated and probabilities are calculated.

For example, (for previous case):
Original string (str) = "10110"
Number of 1's detected (k) = 3
Number of parameters (n) = 5
P = k/n => 3/5 => 0.6
α = P * 100 => 0.6 * 100 => 60%

The mean of probability is done to commonly used to calculate central tendency, variance of probability is performed for is average squared differences from the mean and it provides actual value to how much the number in dataset vary from the mean, have units as squared. It represents the degree to which returns vary over the period and at last standard devation probability is square root of variance and it measures that how far apart numbers are in a dataset.

IV. EVALUATION PROCESS

```
Algorithm 1: MPP
Input: MPP= [0/1, 0/1, 0/1, ......(0/1)n]
where n= number of parameters
String representation str="10110"
(for above illustrated example)
Output: Number of 1's denoted by k
Output: Probability of getting the number of 1's and percentage
• Probability (P) = k/n
• Percentage () = (k/n) * 100 or P *100
(count denoted by k)
count (k): initialized to 0
str = "10110"
for each i in length[str] do
    if str[charAt[i]] = '1' then
        count(k) = count(k) + 1
    end
    i = i + 1
end
// for finding probablity
(length[str] can be written as n)
P = k / length[str]
// for finding percentage
(alpha denoted by )
alpha () = P * 100
return
end procedure
```

Algorithm 1: MPP generation algorithm for sample substring "10110"

It bears same units as provided in dataset. If spread is low that is less standard deviation then there will be low volatility and vice-versa for high spread. The tables 5, 6and graphs obtained are shown in fig 9 and 10 respectively.

Overall Calculation: (For Ungrouped Data)

- Mean ($\bar{x}$):
  for i=1 to n-
  $\bar{x} = (\Sigma x_i) / n$
  $\bar{x} = 0.67$

- Variance (σ^2):
  $\sigma^2 = 1/n \, \Sigma (x_i - \bar{x})^2$
  $\sigma^2 = 115.63$

- Standard Devation (σ):
  $\sigma = \sqrt{1/n \, \Sigma (x_i - \bar{x})^2}$
  $\sigma = 10.75$

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Table 3: Dataset for testing MPP

S No	No. of Profiles	No. of MPP formed	No. of institutions	No. of years	No. of Branches	No. of HOS/DS	No. of LE/LEN	P
1.	5	10	1	1	1	1	1	1.000
2.	5	10	2	1	1	1	1	0.880
3.	10	45	2	1	1	1	1	0.882
4.	15	105	2	1	1	1	1	0.895
6.	5	10	3	1	1	1	1	0.840
7.	10	45	3	1	1	1	1	0.845
8.	15	105	3	1	1	1	1	0.857
10.	5	10	2	1	2	1	1	0.632
11.	10	45	2	1	2	1	1	0.655
12.	15	105	2	1	2	1	1	0.692
14.	5	10	3	1	3	1	1	0.611
15.	10	45	3	1	3	1	1	0.639
16.	15	105	3	1	3	1	1	0.656
10.	5	10	2	2	2	1	1	0.452
11.	10	45	2	2	2	1	1	0.478
12.	15	105	2	2	2	1	1	0.489
14.	5	10	3	3	3	1	1	0.424
15.	10	45	3	3	3	1	1	0.433
16.	15	105	3	3	3	1	1	0.446
10.	5	10	2	2	2	2	1	0.232
11.	10	45	2	2	2	2	1	0.257
12.	15	105	2	2	2	2	1	0.290
14.	5	10	3	3	3	3	1	0.202
15.	10	45	3	3	3	3	1	0.231
16.	15	105	3	3	3	3	1	0.257
17.	5	10	2	2	2	2	2	0.022
18.	10	45	2	2	2	2	2	0.054
19.	15	105	2	2	2	2	2	0.098
20.	5	10	3	3	3	3	3	0.014
21.	10	45	3	3	3	3	3	0.039
22.	15	105	3	3	3	3	3	0.047

Thus, there is increase in probability (α – accuracy) when no. of profiles or parameters like institutions/ branches/ year/ HOS/ DS/ LE/ LEN matched for different profiles are similar. Same can be implemented for 'n' number of parameters of surplus MPP's for achieving better accuracy. Refer to figure 9 and 10.

Table 4: Table for generating graph for variuos no. of profiles

S No	No. of profiles	Mean probability $\bar{x}(P)$	Variance probability $\sigma^2(P)$	Standard Deviation $\sigma(P)$
1.	5	0.48	20.43	4.52
2.	10	0.45	91.20	9.55
3.	15	0.49	210.54	14.51

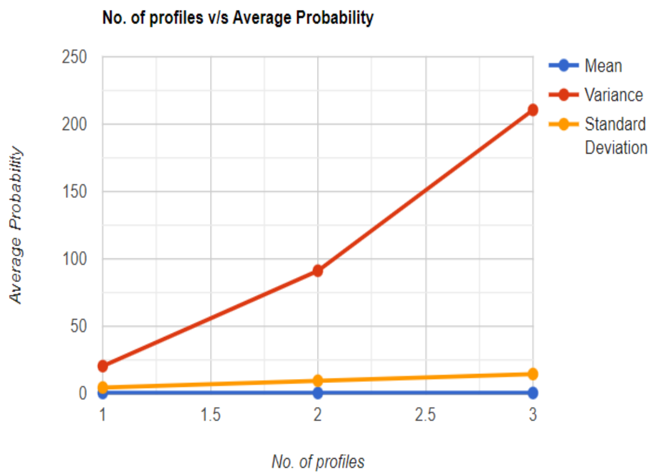

Figure 8: No. of Profiles v/s Average Probability

Table 5: Table for generating graphs for different parameters

S No	No. of institutions/ branches/ year/ HOS/DS/ LE/LEN	Mean probability $\bar{x}(P)$	Variance probability $\sigma^2(P)$	Standard Deviation $\sigma(P)$
1.	1	0.92	0.0064	0.08
2.	2	0.47	2.34	1.53
3.	3	0.43	6.60	2.57

Table 6: Table for generating graphs for different parameters

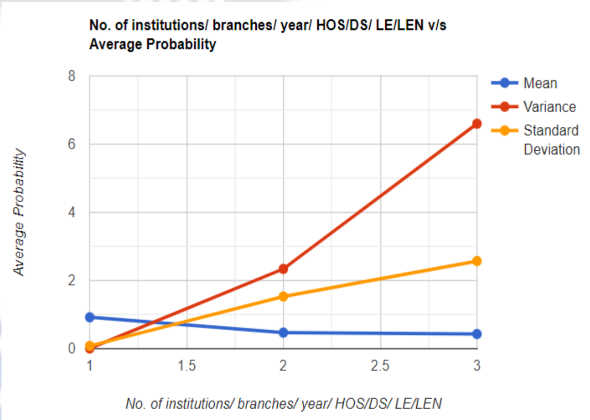

Figure 9: No. of instituions/ branches/ year/ HOS/ DS/ LE/ LEN v/s Average Probability

After getting probability the scale in figure 11 and can be used to denote the nearest value of it and in figure 12 the scale is used to predict the probability in percentage.

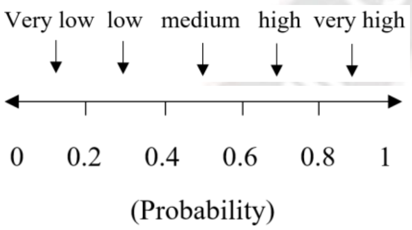

Figure 10: Scale for predicting nearest value of probability

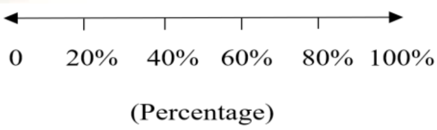

Figure 11: Scale for predicting the percentage

As, the value obtained cannot be deduced to elite extent and to remove the errors the concept of fuzzy set is used refer to figure 13. A chart of a set of real numbers (xi) is known as a fuzzy set with (x_i) onto membership values (u_i)

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which commonly fall in the span of [0, 1] and It is useful tool to portray circumstances in which the data is unclear. It levers by assigning a degree to which a specific object fit in set. Suppose value obtained is 0.424 then by using fuzzy set the descriptive value can be obtained like – 0.424 belongs to low fuzzy set which is having a membership function of 0.1 and it also belongs to medium fuzzy set with a membership function of 0.9. Thus on basis of priority the précised area i.e can be fetched. Therefore, for a particular value the MPP can treated as medium

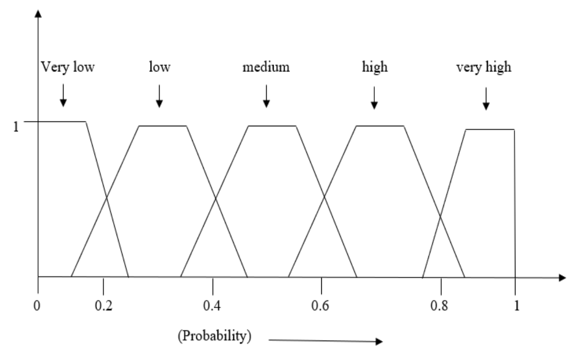

Figure 12: Fuzzy set for obtaining the value

V. APPLICATIONS

The above method can be used in various perspective in which the finite automata plays a dominant role, the regular expression generation, pattern matching, string detection can be covered.

1. Github:

The concept of mutual profile pattern expression can be applied on github user's section. In github people all around the globe share resources and contribute towards open source. In order to manage or scrutinize users according to their contributions and the technologies which they have worked upon, the profile pattern of users can be used. Let's consider an example for this.

Let two user X and Y are open source enthusiasts. X have an android project hosted on github repository andY also wants tocontribute to it. Assuming the technologies as parameters on which the users had worked on,

Let user X parameters be:
[Android Development, Java, Machine Learning, Artificial Intelligence, Python]

Let user Y parameters be:
[Android Development, Java, Swift, Artificial Intelligence, Python]
So MPP for X and Y will be = "11011"
k (number of 1's) = 4
Similarity index(S) in terms of contribution and working experience will be = k/n (where n represents number of parameters)
Thus, S = 4/5 => 0.8
Hence both the users can check the similarity percentage of each other which can help in their future assimilation of projects and work.
So considering above example, this concept can be used with any number of parameters (technologies) and it will help users in analyzing work or contribution done by other users in similar fields.
However, in this paper we have not tested the impact of this approach on the accuracy of other social network platforms, such as Facebook, Instagram and Twitter. We hope that the data presented in the paper can help researchers better understand the current state of MPP's.

VI. CONCLUSION AND FUTURE WORK

With two or three regular expressions, the people had been verified and matched. The program was able to speed up the matching process. This can be considered a good result for a person with various parameters. Another thing to note is that it can be further improvised by involving the machine learning models like random forest, SVM, etc. Involvement of neural network in field of deep learning can fetch some remarkable results.

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