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PNTRS:
Personalized News and Tweet Recommendation System

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ABSTRACT

A news recommendation system not only must recommend the latest, trending, and personalized news to the users but also give opportunity to know about the people's opinion on trending news. Most of the existing news recommendation systems focus on recommending news articles based on user-specific tweets. In contrast to these recommendation systems, the proposed Personalized News and Tweet Recommendation System (PNTRS) recommends tweets based on the recommended article. It firstly generates news recommendation based on user's interest and twitter profile using the Multinomial Naïve Bayes (MNB) classifier. Further, the system uses these recommended articles to recommend various trending tweets using fuzzy inference system. Additionally, feedback-based learning is applied to improve the efficiency of the proposed recommendation system. The user feedback rating is taken to evaluate the satisfaction level, and it is 7.9 on the scale of 10.

KEYWORDS

Feedback-Based Learning, Fuzzy Inference System, Information Filtering, Social Media, Twitter, User Preferences

INTRODUCTION

A news article is not just a fact or information, but it is the information that affects people. It affects the way people live their lives, performs their jobs, and make decisions. A news article tells people what is happening around them that they must be aware of as a resident, a human being, a community member, and as a part of the socio-economic, biological and political system.

Online news readers frequently face information overload due to several news websites, and these news websites keep regularly increasing (Tiwari, 2018). From the tons of available news websites (or portals) online, containing hundreds of news articles from around the globe, what makes a news

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website stand out from others is how precisely and efficiently it delivers the news articles to the users. In addition, finding news relevant to the users is equivalent to finding a needle in a haystack.

Moreover, every individual is different from others in terms of taste, personality, and needs, and therefore their interest in news articles differs from others. Some people like to read articles about politics while some like sports, arts, technology, environmental changes, etc.

User needs to find the precise, trending and specific news which interest them. They may also be interested in the discussions and opinions of other people on the current news articles. However, due to the massive amount of information, it is tedious to find relevant news and discussions. There are several news aggregator apps available such as Apple News, News360m, Yahoo News, etc. which provide user with several news articles but they do none or a very little personalization of the contents. These apps generally use the static user profile or recent social media trends to notify the news article to the users (Tiwari, 2018). The news recommendation system (RS) may solve this problem by recommending personalized news from the most popular resources. A news recommendation system recommends the news article to the user by taking into various parameters provided to it as input.

The primary goal of a recommendation system is to learn the user behavior and preferences and generate the meaningful recommendations (Adomavicius, 2005; Burke, 2002). Under the hood, recommendation systems rely on various algorithms to determine what should be recommended. Some algorithms look at keywords or editorial tags to find matching content, while others analyze the content more deeply, on a semantic level. Some consider the diversity and novelty of the items in context, while others gather a range of tracking data to personalize recommendations to each user dynamically (Adomavicius, 2011; Adomavicius, 2005). However, the best systems leverage a hybrid of all of the above.

In current era, twitter has become an important source for disseminating the news and opinion across the globe. The news preferences of users are highly affected by the recent trends in social media. Therefore, the news article recommendations considering the latest twitter trends and user preferences will make it convenient for users to get relevant information. This will not only help users to gain knowledge about the current issues but also allow them to read the opinion and viewpoints of other people.

This work, therefore, proposes a personalized news and tweet recommendation system (PNTRS). The proposed approach is divided into a personalized news recommendation system (PNRS) and a personalized tweet recommendation system (PTRS). The PNRS deals with the personalization of news articles, categorizing news articles, and improving the user profile using feedback-based learning. The PTRS, on the other hand, uses the fuzzy inference system to recommend personalized tweets to the user based on the recommended news article by PNRS. Most of the recent work in the field of news recommender mostly focuses on recommending the news article which are trending on twitter. In contrast to these, proposed work not only recommend trending news article which are personalized for specific user but also recommends the tweets which are related to the recommended news article.

The rest of the paper is organized in sections named as related work, methodology, experimental results and conclusions.

Related Work

RS domain has been well explored in the past couple of decades (Tiwari, March 2015; Tiwari, 2012; Adomavicius, 2011; Berjani, 2011; Adomavicius, 2005; Burke 2002). A lot of contributions can be found in the field of news recommendation systems, and some work can be found in the tweet recommendation system as well. Some of the relevant literature is presented in this section.

A hybrid intelligent model for classification of news articles known as Daily Learner was proposed in (Billsus, 1999). This work focuses on the personalization of articles and the ubiquity of information. The dataset of 300 users was used to evaluate the system. An approach for analyzing the user behavior from his/her browsing pattern is used to news recommendation system in (Liang, 2002). This proposed time-based method for analyzing the user behavior outperforms the headlines-based approach for the news recommendation system. Another work based on the click behavior pattern of users can be found in (Liu, 2010). This work develops a collaborative filtering-based news recommendation system and considers the fact that the news interest of user changes over time. The work presented in (Bomhardt, 2004) called NewsRec is an RS based on SVM.

A mobile news RS called MONERS (Lee, 2007) used the news article attributes and user preferences in context to the news article categories. The ontology-based news RS is proposed in (IJntema, 2010; Cantador, 2008). The news RS presented in (Li, 2010) uses the contextual bandit problem for the recommendation. The event-based news clustering and social media-based ranking are used to develop NewsClu in (Weber, 2013). Work presented in (Liu, 2007) presents a news ranking method using news ranking function, citation count, freshness, semantic relevance of the article, and degree of authority. A personalized news recommendation system was proposed in (Liu, 2016), which uses hybrid collaborative filtering. Deep neural network-based approach for news recommendation can be found in (Park, 2017), and a multi-channel deep fusion approach is used in (Lian, 2018; Liu, 2018; Kumar, 2017;). Location aware news RS is presented in (Chen, 2017), which makes use of localized semantics.

The news recommendation based on twitter is gaining popularity in the recent past. A twitter-based real time new recommendation system was presented in (Phelan, 2009). This work uses the microblogging patterns of user for prompting the news stories. Authors in (Phelan, 2011) proposed Buzzer, which exploits the conversation on twitter and ranks the RSS subscriptions. In (Abel, 2011), the authors identified the topics and the entities used in the tweets and proposed a framework. The personalized news RS was presented in (Jonnalagedda, 2013), which ranks the news articles based on user preferences.

The work presented in (Mahalakshmi, 2017) studies the influential user from tweeter data to promote the product and services. Tweet readability and polarity for each user are mined, and their positions in different network topics are analyzed. The work in (Tiwari, 2018) infers the user tweets' implicit user preferences and uses the fuzzy clustering to identify user preferences.

In (Krestel, 2015) the tweet recommendation based on a news article is presented. It uses the Dirichlet method for comparing tweets and news articles. A tweet credibility assessment model is proposed in (AlRubaian, 2016).

In contrast to the existing work, this work presents a recommendation system that recommends personalized news and personalized tweets relevant to the recommended news article.

Methodology

The block diagram of the proposed Personalized News and Tweet Recommendation System (PNTRS) is shown in Figure 1. The PNTRS combines two recommendation systems: Personalized News Recommendation System (PNRS) and Personalized Tweet Recommendation System (PTRS). The user preferences, user twitter profile, and news articles are the inputs for PNRS, and it provides personalized recommendations for news articles to the individual user as output. The output of PNRS, i.e., the set of recommended articles for a user, is taken as input by PTRS and produces personalized tweets recommendations for the user. These two components (RS) are described in detail in subsequent sections.

Personalized News Recommendation System (PNRS)

PNRS recommends personalized and trending news articles to the user. The block diagram of PNRS is shown in Figure 2. The major components of PNRS include profile builder, news classifier, news ranker, and feedback-based learner. The user preference and user's twitter profile are used by the profile builder to learn the user preferences and build the user matrix. The news articles from the NEWS API are used by the news classifier to categorize the news articles, and it is called a news matrix. The user matrix and news matrix build are used by the news ranker for ranking the news article to suit the user preferences. However, to improve the user profile with a continuous-time, feedback-based

Figure 1. Block diagram of PNTRS

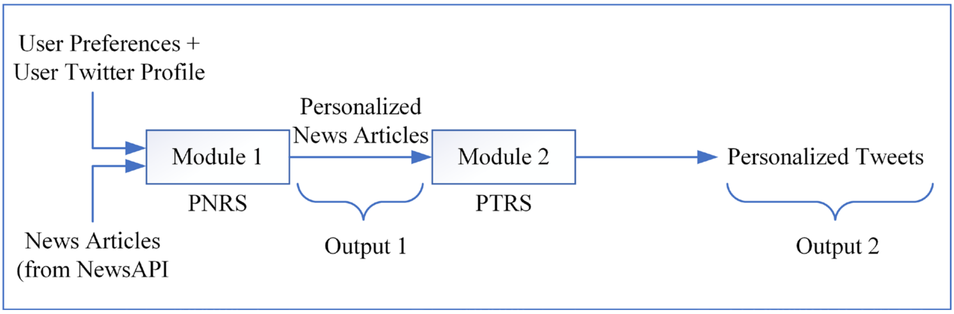
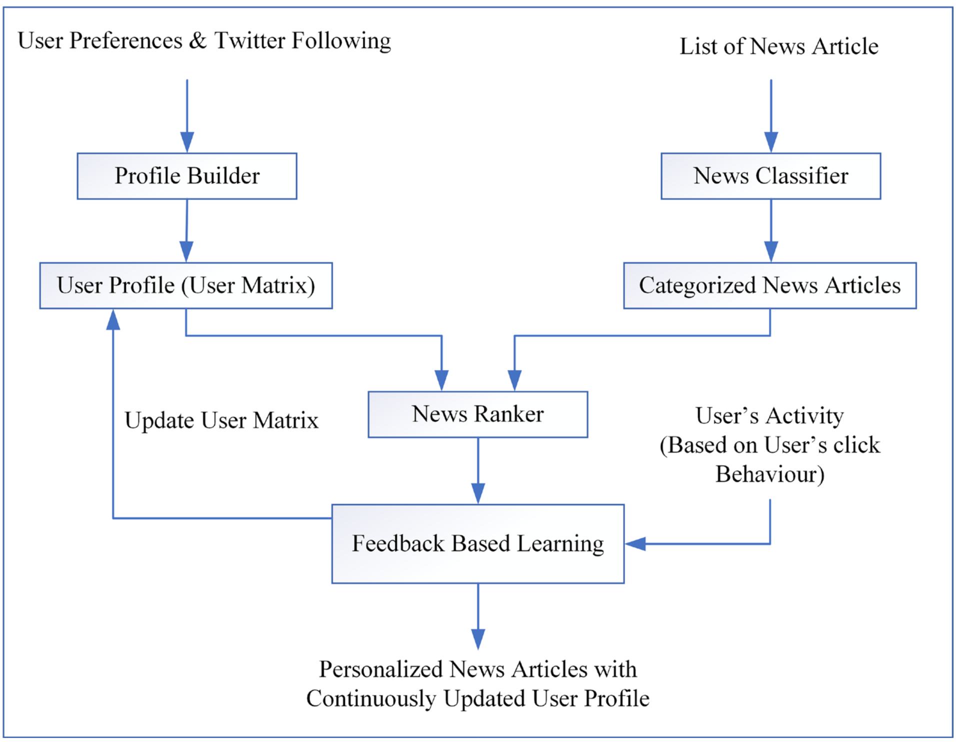


Figure 2. Block diagram of PNRS



learning is applied to update the user matrix based on the user click behavior. Hence, PNRS gives the personalized list of news articles with the continuously updated user profile. All these modules are implemented using python APIs.

DATASET

A balanced data set with sufficient news articles with their categories are not freely available for experiments and testing. Therefore, two datasets are merged together for the evaluation of the proposed RS. The two datasets used for experiments are obtained from Kaggle (Mishra, 2018) and BBC websites (Green, 2006). The BBC dataset contains around 2.2K news articles obtained from the BBC website, which falls into five categories: business, entertainment, politics, sports, and technology.

The Kaggle dataset contains around 200k news headlines obtained from HuffPost. These two datasets are combined and made compatible. However, the merging provided some skewness and resulted in unbalanced data, making it biased toward a certain category. After merging the two data sets, the number of training instances in each data set for every category was different, and this is the reason for the unbalanced data set. To remove the skewness, the minimum number of articles from all the categories is found. This is set as the threshold for adding training instances for a specific category. The model trained on this dataset could be used to identify tags for untracked news articles or identify the type of language used in different news articles.

Profile Builder

The working of the profile builder is shown in Figure 3. The user is first asked for his/her topmost three preferences explicitly. This is used to build the initial profile of the user and address the new user problem. Later, the user's Twitter account is used to build the final profile and recommend the personalized news articles through PNRS. Using the Twitter API, the list of people followed by the particular user is extracted. For each followed person/ twitter account, the same name Wikipedia page is searched, and if it exists, then the keywords of the same are extracted. These keywords are finally sent to train a machine learning (ML) model, which then predicts the interest of user u in each category. The steps involved in obtaining the final user profile from the twitter account of the user are as follows:

Get the followed accounts: Initially, the current user's (u) twitter username is used to find the access keys for that user. These two are used to obtain the user_id(s) (v_0 *to* v_n) of all the n accounts followed by the user u. The details that can be found along with the user_id of followed account (v_0 *to* v_n) are usernames, twitter handle, verified, followed count, follower count, description, etc.

1. **Find the correct name for each v_i:** The name of each user v_i obtained in the previous step may contain misspelled words, alternate spellings, or short forms (initials of a person). Wikipedia database's resolve redirects feature is used to obtain the correct names for each user v_i.
2. **Retrieve the Wikipedia page for each v_i:** The Wikipedia page corresponding to each user v_i is retrieved.
3. **Extract keyword for user v_i**: The first line of each Wikipedia page retrieve is extracted. The list of keywords is obtained from this.
4. **Train the ML model to predict interest in the category of user u:** The keywords extracted are used by the ML model to predict the interest of user u in each category. This forms the user matrix. The sample user matrix is shown in Table 1. The experiments in this work use five categories.

News Classifier

The working of the news classifier is shown in Figure 4. This component categorizes the news articles in a specific category. It takes news articles from News API. The News API (HTTP REST API) is a source that is used to search and retrieve live news articles from the web. This API can help to answer questions like "what top stories is the NY Times running now?" Or "what news articles were published about the next iPhone today?" etc. The news articles can be searched using any combination of date of release, keywords, source name, language, etc. A classifier is used to generate a news matrix having five categories, and the probability of each category for every news article is predicted.

In order to categorize the news articles and form the news matrix as well as user matrix for different categories, a model is required, which can train itself and improve the performance over the period of time. Firstly, the article headline is fetched using the News API, and keywords are extracted, which are again given as an input to the trained classifier model, which helps to predict the probability of the same news article in each category. Once the article category is found, the new

Figure 3. The profile builder

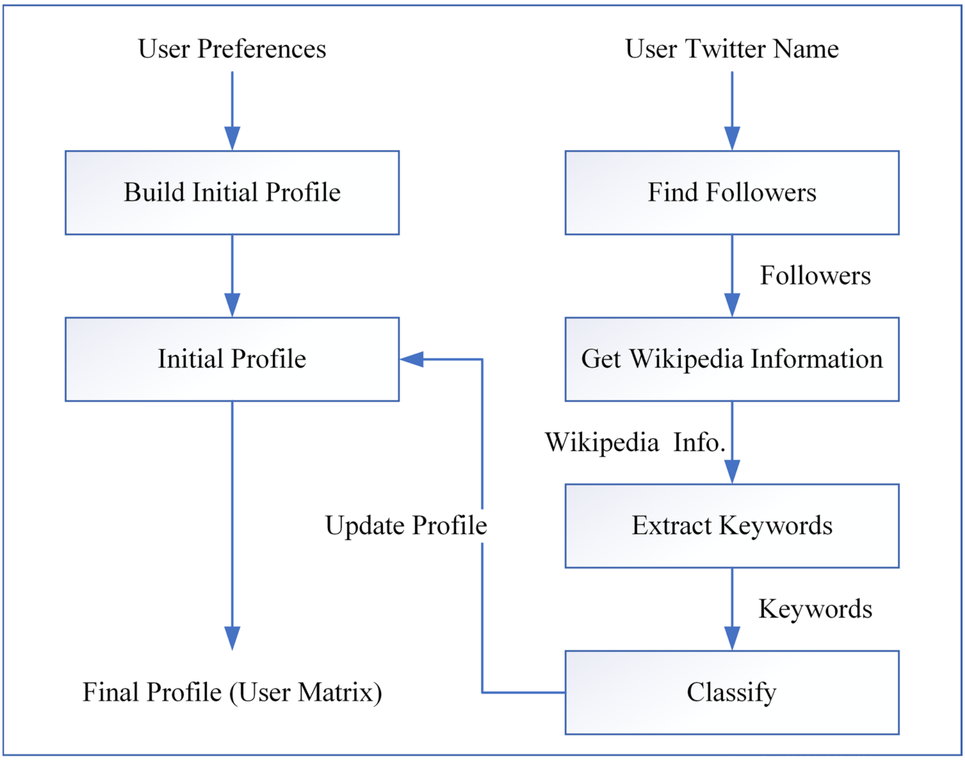


Table 1. Sample user matrix

	Cat_1	Cat_2	Cat_3	….	Cat_n
u_1	0.41	0.32	0	….	0.13
u_2	0.11	0.26	0.41	….	0.10
…	…	…	…	…	…
u_n	0.36	0.41	0.01	….	0.22

article shall be recommended to the users accordingly based on the further design of the modules. For this, various machine learning models like multinomial naïve bayes (MNB) classifier, linear support vector machine (SVM), radial basis kernel (RBF) SVM, Logistic Regression, and Random Forest are applied, and their accuracy is compared. The MNB classifier showed better accuracy than others, and therefore it is chosen for further experiments.

The steps involved in obtaining the news matrix from News API are as follows-

1. **Extract the headline from each article a_i:** The articles retrieved form NEWS API are used to extract their headlines.
2. **Extract keywords:** The keywords for each headline are extracted.
3. **Train the ML model to predict category for each article a_i:** The keywords extracted are used by the ML model to predict the category for each article. This forms the news matrix. The sample news matrix is shown in Table 2.

Figure 4. The news classifier

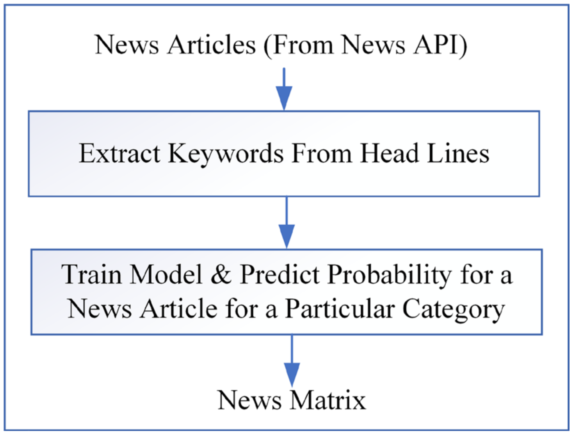


Table 2. Sample news matrix

	Cat_1	**Cat_2**	**Cat_3**	**….**	**Cat_n**
a_1	0.4	0.3	0	….	0.1
a_2	0	0.2	0.6	….	0.1
…	**…**	**…**	**…**	**…**	**…**
a_n	0.3	0.4	0	….	0.2

News Ranker

For each user, the news articles which are to be recommended shall be ranked in the order of their preferences. For this, the similarity between the user matrix and the news matrix is computed using the Pearson correlation coefficient.

The Pearson's correlation coefficient returns the value [+1, -1] where +1 corresponds to the strongest positive correlation, -1 corresponds to strong negative correlation, and values towards 0 indicate week correlation. The Pearson's method is popularly used as similarity measure in information filtering and recommendation system domain. It is the ratio of the covariance of the two variables and the product of their standard deviations. Pearson's correlation is computed using equation (1), where r_{xy} is the correlation between variables X and Y. The cov (X, Y) is the covariance between variables X and Y, σ_X and σ_Y represents the standard deviations of variable X and Y, respectively. This module outputs a ranked list that helps to recommend the personalized news articles to the user. The sample correlation matrix is shown in Table 3.

Table 3. correlation coefficient for user u

News article title	**Correlation for user *u***
Priyanka Gandhi Vadra says *she* will contest *polls if Congress asks her*	0.785
Kartik Aaryan showered with marriage proposals	0.378
…	…
NASA updates Artemis Plan for returning astronauts to the Moon in 2024	0.011

$$r_{XY} = \frac{cov(X,Y)}{\sigma_X \sigma_Y} \tag{1}$$

Feedback-Based Learning

There is a chance that user preferences might change over a period of time. Therefore the RS shall be efficient enough to inculcate those preferences and recommend personalized news to the user. To achieve this, feedback-based learning is applied to improve the user matrix based on the number of clicks in each category.

Once the user matrix is updated, the PNRS shall display a random number of articles from different categories to the user. Hence, a *show matrix* consisting of the number of articles displayed for each category and a *click matrix* defining the number of articles which the user has clicked or selected to read from respective categories is formed. Based on this, the following ratio is calculated using equation (2).

$$Ratio = \frac{[ClickMatrix]}{[ShowMatrix]} \tag{2}$$

This gives the ratio for each category for a particular user, which is then compared with the final user matrix to build the updated one. After comparison, if the ratio explains that there has been an increase in the interest for a particular category, a higher amount of factor is associated with the category such that the probability of the respective category increases in the updated user matrix. Similarly, if the ratio explains that there has been a decrease in the interest for a particular category, the factor is associated such that the probability of the respective category decreases in the updated user matrix. Therefore, based on the clicks of the user, the final user matrix is updated.

Personalized Tweet Recommendation System (PTRS)

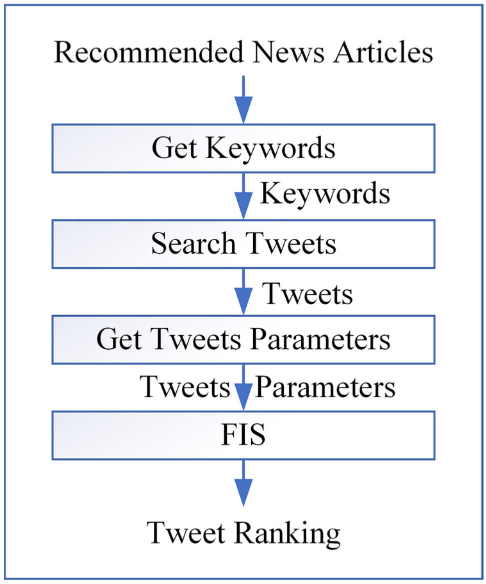
PTRS is developed to recommend the most relevant tweets for personalized news articles. The Fuzzy Inference System (FIS) is used on the news articles retrieved from PNRS for tweet recommendation.

The working of PTRS is shown in Figure 5. Once user-specific news is retrieved by PNRS, the keywords from that news article are extracted. After this, relevant tweets are searched based on the keyword extracted. The tweets are then applied to the Fuzzy Inference System, from which a rating is obtained for each tweet individually. The tweets are sorted on the basis of rating and the top most relevant tweets with the highest rating are recommended to a user.

A FIS provides the mapping from a given set of inputs to an output. The fuzzy information system is used in decision making. It uses rules of the form "IF… Then…" which may be connected with AND / OR operators. Input to the FIS can be crisp or fuzzy, but the output is fuzzy, which is further de-fuzzified to crisp values. A FIS consists of inputs, fuzzification unit, if then rules (knowledge base), decision making unit, defuzzification unit, and output variables (Tiwari, June 2015). The FIS works as follows:

1. Input variables are fuzzified using the membership functions defined for every variable.
2. Antecedent matching is performed to compute the strength of rule for given input values for each rule.
3. The consequent of the rule is determined. This is done for all the rules in parallel. It combines the strength computed in the previous step to determine the membership of output for each rule.

Figure 5. Block diagram of PTRS



4. All the consequents obtained for different rules are aggregated to find the output.
5. Defuzzification of the output variable is performed.

The design of the fuzzy inference system for tweet ranking is explained as follows.

Input Variables: Five input variables are used for FIS: 1) tweet occurrence, 2) ratio of likes/ times, 3) ratio of likes/followers, 4) ratio of retweet/followers 5) ratio of retweet times.

Output Variable: The output variable is the rating of the tweet.

Fuzzy Rules: The sample fuzzy rules are shown as following –

If the occurrence is high, then rating is high.

If the occurrence is poor, then rating is low.

If the ratio of likes/ followers and ratio of retweets/ followers is low, then the rating is low.

If the ratio of retweets/ followers and retweets/ time is average, then rating is medium.

If the ratio of likes/ time and retweets/ time is good, then rating is high.

If the ratio of likes/ follower and retweets/ follower is good, then rating is high.

Evaluation of Antecedent: If the fuzzy rules are connected with AND then the fuzzy min method is used, and if they are connected with OR then the fuzzy max method is used.

Implication of Rule and Aggregation of Output: Fuzzy product method is used for implication, and the fuzzy max method is used for aggregation.

Defuzzification: The centroid method is used for defuzzification of output.

Experimental Results

The experiments are performed on ten real users. They are registered on PNTRS and their profile is used to build user matrix. Only those ten users are considered for evaluation of proposed system who has given consent to use their profile information for experiments of PNTRS. In future, the experiments on more users will be performed once they register on the system and give their consent for the same. The results obtained at the various stages in PNTRS are discussed here.

Results of PNRS

Before implementing the PNRS, a classifier needs to be selected. The classifier is selected after performing different experiments. Figure 6 shows a graph that compares the accuracy of different machine learning models: MNB classifier, Random Forest, Logistic Regression, Linear SVM, and RBF SVM applied on the news dataset. The MNB classifier gave the highest accuracy, as it can be observed from the Figure 6. Therefore, the MNB classifier is chosen to be the classifier model in PNRS.

The sample output of the profile builder is shown in Figure 7. This is the user profile matrix before applying feedback-based learning. This profile is built based on categories of interest entered by the user and then updating this profile using the twitter account of the user. This profile will be further updated using feedback-based learning.

Figure 8 shows the output of the news classifier module saved in a csv file. The csv file has three columns as title, URL, and matrix. The title shows the headline of the particular news article, and its source is being stored in the URL column of the csv file. The matrix column contains five commas separated values where each value represents the predicted probability of the respective category. The matrix is termed as news matrix having the following categories: [‘business’, ‘entertainment’, ‘politics’, ‘sport’, ‘tech’].

Figure 9 shows the ranking of news articles in the csv file. The csv file has four columns as title, URL, news matrix, and correlation factor. The correlation factor shows the correlation between the user matrix and the news matrix, which has been calculated using Pearson’s Correlation Coefficient. The higher the correlation value, the higher the news ranking would be.

Figure 7 and Figure 10 respectively show the sample user matrix before (generated by profile builder) and after applying the feedback-based learning. In Figurer 10, the updated user matrix tells the number of times the user matrix has been updated. This user matrix may or may not be equal to the initial user matrix built using the profile builder module. The update user matrix depends on user interaction with the system (i.e., the number of clicks made by the user on the news articles).

Figure 6. Comparison of different classifier in terms of accuracy

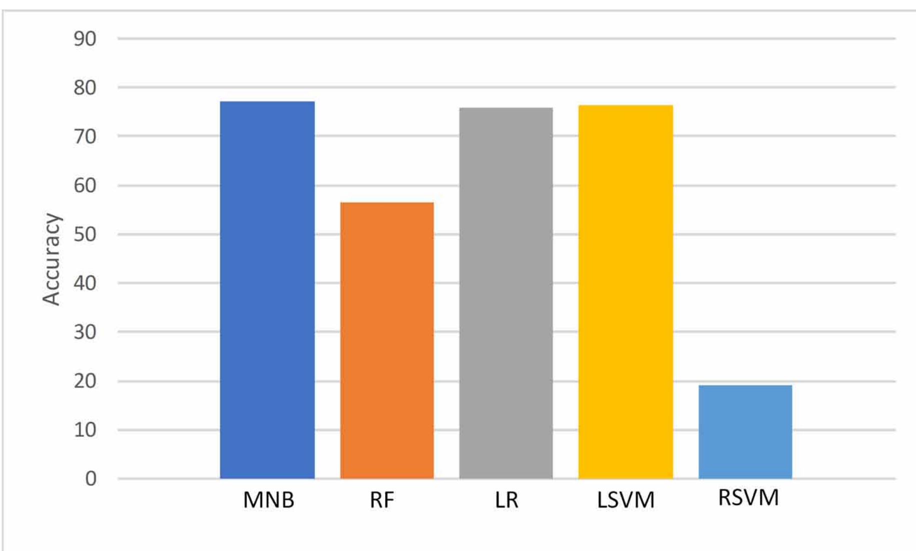


Figure 7. User matrix of ten sample (before applying feedback learning)

	user_name	user_matrix	times_updated
2	raman	0.1706, 0.3269, 0.2805, 0.2111, 0.0109	0
3	deepak	0.2028, 0.338, 0.0904, 0.1311, 0.2378	0
4	dadhich_vyoma	0.024, 0.4603, 0.3467, 0.0761, 0.0929	0
5	arjun	0.2057, 0.2178, 0.2445, 0.1066, 0.2254	0
6	hamid	0.1323, 0.2918, 0.2979, 0.114, 0.164	0
7	nikhil	0.1917, 0.0321, 0.1586, 0.3633, 0.2544	0
8	chandan	0.2119, 0.1871, 0.2251, 0.2369, 0.1391	0
9	stan_vj	0.0601, 0.1588, 0.1339, 0.1934, 0.4537	0
10	sagar	0.3777, 0.2044, 0.1312, 0.1328, 0.1539	0
11	trump	0.2716, 0.3353, 0.0194, 0.2713, 0.1024	0

Figure 8. News matrix for trending news

	Title	URL	Matrix
2	IPL 2019 Live Score, Kolkata Knight Riders vs Kings XI Punjab: KKR on Top as Agarwal Departs - Ne	https://www.news18.com/cricketnext/news/ipl-2019-live-score	0.0, 0.1, 0.1, 0.8, 0.0
3	Lok Sabha poll tracker LIVE: PM Modi's address to nation being examined, says EC - Moneycontr	https://www.moneycontrol.com/news/india/lok-sabha-polls-g	0.1, 0.1, 0.7, 0.0, 0.1
4	De Villiers unfazed by the Bumrah threat - Cricbuzz	https://www.cricbuzz.com/cricket-news/107315/de-villiers-unf	0.0, 0.6, 0.0, 0.4, 0.0
5	Kartik Aaryan showered with marriage proposals, one asks for his advance booking - Hindustan	https://www.hindustantimes.com/bollywood/kartik-aaryan-sh	0.0, 0.4, 0.6, 0.0, 0.0
6	Election Commission to Look Into 'Urgency' of PM Modi's Address to Nation Fortnight Before Lol	https://www.news18.com/news/politics/election-commission-	0.2, 0.0, 0.7, 0.0, 0.1
7	'The Elder Scrolls: Blades' Is Launching Early, and Is Available to Download on the New Zealand /	https://toucharcade.com/2019/03/27/the-elder-scrolls-blades-	0.0, 0.2, 0.0, 0.0, 0.8
8	Sultan Azlan Shah Cup: India thrash Canada 7-3 to set up final with South Korea - Times of India	https://timesofindia.indiatimes.com/sports/hockey/top-stories	0.0, 0.2, 0.1, 0.7, 0.0
9	Priyanka Gandhi Vadra Says Will Contest Polls If Congress Wants - NDTV News	https://www.ndtv.com/india-news/priyanka-gandhi-vadra-says	0.3, 0.0, 0.7, 0.0, 0.0
10	Vedanta reports oil discovery in KG basin - Livemint	https://www.livemint.com/industry/energy/vedanta-reports-oi	0.8, 0.1, 0.1, 0.0, 0.0
11	More children â€“ more heart trouble for parents - The Asian Age	https://www.asianage.com/life/health/270319/more-children-	0.1, 0.1, 0.1, 0.0, 0.7
12	'Made presentations on A-SAT during UPA-II, did not get response,' says former DRDO chief VK S	https://timesofindia.indiatimes.com/india/made-presentations	0.1, 0.0, 0.7, 0.0, 0.2
13	OnePlus 7: Video gives closer look at triple rear camera setup, improved design - Hindustan Tim	https://www.hindustantimes.com/tech/oneplus-7-leaks-again-	0.1, 0.1, 0.1, 0.0, 0.7
14	Hearing Loss Before 50 May Raise Drug Abuse Risk - News18	https://www.news18.com/news/lifestyle/hearing-loss-before-5	0.7, 0.0, 0.0, 0.0, 0.3
15	Why is NASA returning astronauts to Moon? - India Today	https://www.indiatoday.in/education-today/gk-current-affairs/	0.1, 0.0, 0.0, 0.0, 0.9
16	Huawei P30 Lite With Triple Rear Cameras Up for Pre-Orders Ahead of Launch - NDTV	https://gadgets.ndtv.com/mobiles/news/huawei-p30-lite-price	0.1, 0.3, 0.0, 0.0, 0.6
17	Maruti Suzuki to source Brezza from Toyota, board clears two more proposals - Moneycontrol.c	https://www.moneycontrol.com/news/technology/auto/marut	0.2, 0.0, 0.0, 0.0, 0.8
18	IPL 'Mankading' row: Ashwin didn't cheat, so why all the brouhaha? - Times of India	https://timesofindia.indiatimes.com/blogs/a-good-sport/ipl-ma	0.0, 0.0, 0.6, 0.4, 0.0
19	Why Jet Airways flies when Kingfisher Airlines couldn't - Times of India	https://timesofindia.indiatimes.com/business/india-business/v	0.3, 0.0, 0.0, 0.0, 0.7
20	Alia Bhattâ€™s Sabyasachi sari is just right for your BFFâ€™s cocktail party - VOGUE India	https://www.vogue.in/wedding-wardrobe/collection/alia-bhatt	0.0, 1.0, 0.0, 0.0, 0.0
21	Exclusive: Meet The Aspiring Doctor Whoâ€™s Also a Pro PUBG Mobile Gamer - News18	https://www.news18.com/news/tech/exclusive-meet-the-aspir	0.0, 0.0, 0.0, 0.0, 1.0
22	Lok Sabha Elections 2019 LIVE: National security may not be an issue for those who do 'mahami	https://economictimes.indiatimes.com/news/elections/lok-sab	0.1339, 0.084, 0.293, 0.237, 0.2522
23	World Malaria Day: What is the 'Landmark' Vaccine Rolled out by Malawai	https://www.news18.com/news/india/world-malaria-day-wha	0.1623, 0.1495, 0.2454, 0.2024, 0.2404
24	Rajasthan Royals predicted XI against KKR: Tactical change expected against Kolkata Knight Rider	https://www.hindustantimes.com/cricket/rajasthan-royals-pre	0.2449, 0.1581, 0.2186, 0.1818, 0.1966
25	OnePlus 7 Pro With 8GB RAM and 256GB Storage to Cost Over Rs 55,000	https://www.news18.com/news/tech/oneplus-7-pro-with-8gb-	0.2014, 0.0865, 0.0903, 0.2569, 0.3648
26	Rich and powerful can't run top court, says SC on 'conspiracy' against CJI	https://timesofindia.indiatimes.com/india/supreme-court-orde	0.2064, 0.1187, 0.4449, 0.0907, 0.1393
27	Spurned by Washington, North Korea's Kim Seeks a Friend in Putin at Their First Summit	https://www.news18.com/news/world/spurned-by-washingto	0.1048, 0.3148, 0.3314, 0.1731, 0.0759
28	NASA's InSight Lander captures first 'marsquake'	https://www.asianage.com/science/250419/nasas-insight-land	0.1518, 0.2223, 0.1657, 0.2078, 0.2524

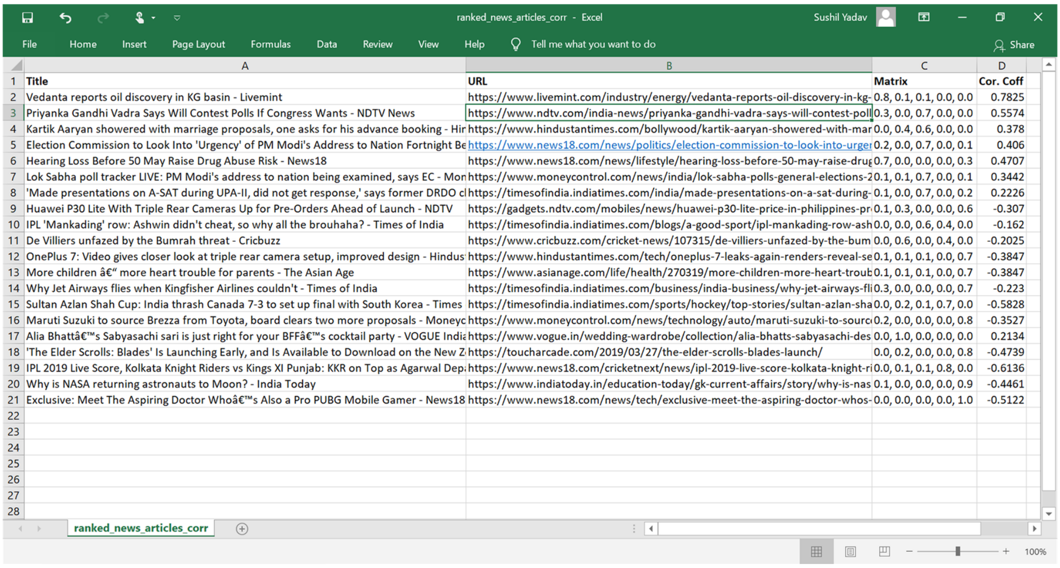
This module has been tested on the user highlighted with a rectangle. This matrix is updated once, as shown in the third column of the highlighted row of Figure 10.

Results of PTRS

The PTRS is evaluated on the same set of ten users. The results obtained for PNRS are discussed here.

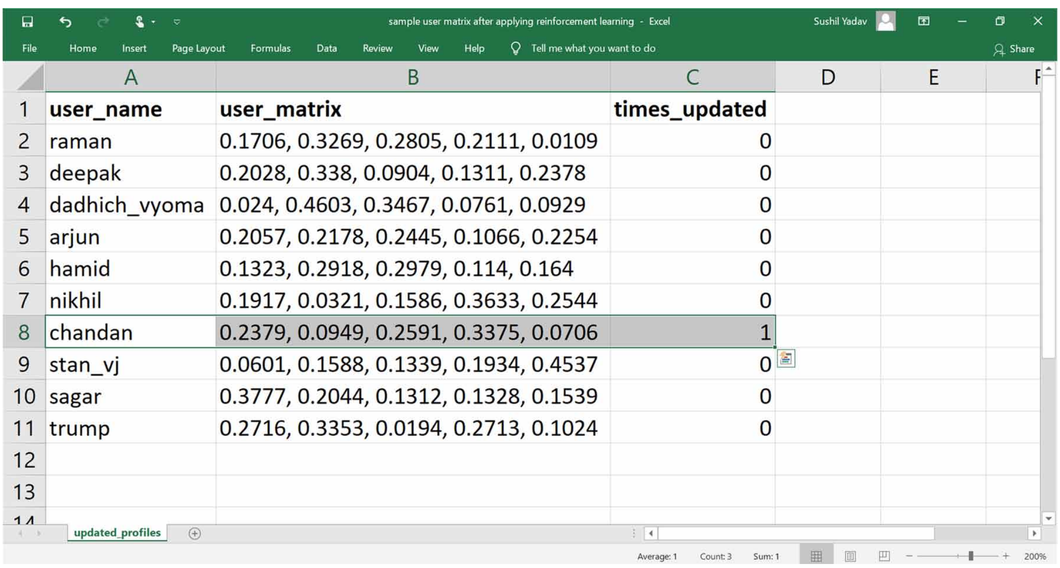
Figure 11 a) shows the relation between the tweet and the number of likes received. In order to filter the best tweets from the ones obtained, it was required to set a few parameters for the inference

Figure 9. Ranking of news articles



Title	URL	Matrix	Cor. Coff
Vedanta reports oil discovery in KG basin - Livemint	https://www.livemint.com/industry/energy/vedanta-reports-oil-discovery-in-kg-	0.8, 0.1, 0.1, 0.0, 0.0	0.7825
Priyanka Gandhi Vadra Says Will Contest Polls If Congress Wants - NDTV News	https://www.ndtv.com/india-news/priyanka-gandhi-vadra-says-will-contest-poll	0.3, 0.0, 0.7, 0.0, 0.0	0.5574
Kartik Aaryan showered with marriage proposals, one asks for his advance booking - Hir	https://www.hindustantimes.com/bollywood/kartik-aaryan-showered-with-mar	0.0, 0.4, 0.6, 0.0, 0.0	0.378
Election Commission to Look Into 'Urgency' of PM Modi's Address to Nation Fortnight Be	https://www.news18.com/news/politics/election-commission-to-look-into-urger	0.2, 0.0, 0.7, 0.0, 0.1	0.406
Hearing Loss Before 50 May Raise Drug Abuse Risk - News18	https://www.news18.com/news/lifestyle/hearing-loss-before-50-may-raise-drug	0.7, 0.0, 0.0, 0.0, 0.3	0.4707
Lok Sabha poll tracker LIVE: PM Modi's address to nation being examined, says EC - Mon	https://www.moneycontrol.com/news/india/lok-sabha-polls-general-elections-2	0.1, 0.1, 0.7, 0.0, 0.1	0.3442
'Made presentations on A-SAT during UPA-II, did not get response,' says former DRDO cl	https://timesofindia.indiatimes.com/india/made-presentations-on-a-sat-during-	0.1, 0.0, 0.7, 0.0, 0.2	0.2226
Huawei P30 Lite With Triple Rear Cameras Up for Pre-Orders Ahead of Launch - NDTV	https://gadgets.ndtv.com/mobiles/news/huawei-p30-lite-price-in-philippines-pr	0.1, 0.3, 0.0, 0.0, 0.6	-0.307
IPL 'Mankading' row: Ashwin didn't cheat, so why all the brouhaha? - Times of India	https://timesofindia.indiatimes.com/blogs/a-good-sport/ipl-mankading-row-ash	0.0, 0.0, 0.6, 0.4, 0.0	-0.162
De Villiers unfazed by the Bumrah threat - Cricbuzz	https://www.cricbuzz.com/cricket-news/107315/de-villiers-unfazed-by-the-bum	0.0, 0.6, 0.0, 0.4, 0.0	-0.2025
OnePlus 7: Video gives closer look at triple rear camera setup, improved design - Hindus	https://www.hindustantimes.com/tech/oneplus-7-leaks-again-renders-reveal-se	0.1, 0.1, 0.1, 0.0, 0.7	-0.3847
More children â€" more heart trouble for parents - The Asian Age	https://www.asianage.com/life/health/270319/more-children-more-heart-troub	0.1, 0.1, 0.1, 0.0, 0.7	-0.3847
Why Jet Airways flies when Kingfisher Airlines couldn't - Times of India	https://timesofindia.indiatimes.com/business/india-business/why-jet-airways-fli	0.3, 0.0, 0.0, 0.0, 0.7	-0.223
Sultan Azlan Shah Cup: India thrash Canada 7-3 to set up final with South Korea - Times	https://timesofindia.indiatimes.com/sports/hockey/top-stories/sultan-azlan-sha	0.0, 0.2, 0.1, 0.7, 0.0	-0.5828
Maruti Suzuki to source Brezza from Toyota, board clears two more proposals - Moneyc	https://www.moneycontrol.com/news/technology/auto/maruti-suzuki-to-sourc	0.2, 0.0, 0.0, 0.0, 0.8	-0.3527
Alia Bhattâ€™s Sabyasachi sari is just right for your BFFâ€™s cocktail party - VOGUE India	https://www.vogue.in/wedding-wardrobe/collection/alia-bhatts-sabyasachi-des	0.0, 1.0, 0.0, 0.0, 0.0	0.2134
'The Elder Scrolls: Blades' Is Launching Early, and Is Available to Download on the New Z	https://toucharcade.com/2019/03/27/the-elder-scrolls-blades-launch/	0.0, 0.2, 0.0, 0.0, 0.8	-0.4739
IPL 2019 Live Score, Kolkata Knight Riders vs Kings XI Punjab: KKR on Top as Agarwal Dep	https://www.news18.com/cricketnext/news/ipl-2019-live-score-kolkata-knight-ri	0.0, 0.1, 0.1, 0.8, 0.0	-0.6136
Why is NASA returning astronauts to Moon? - India Today	https://www.indiatoday.in/education-today/gk-current-affairs/story/why-is-nas	0.1, 0.0, 0.0, 0.0, 0.9	-0.4461
Exclusive: Meet The Aspiring Doctor Whoâ€™s Also a Pro PUBG Mobile Gamer - News18	https://www.news18.com/news/tech/exclusive-meet-the-aspiring-doctor-whos-	0.0, 0.0, 0.0, 0.0, 1.0	-0.5122

Figure 10. Updated user matrix (after applying feedback learning)



user_name	user_matrix	times_updated
raman	0.1706, 0.3269, 0.2805, 0.2111, 0.0109	0
deepak	0.2028, 0.338, 0.0904, 0.1311, 0.2378	0
dadhich_vyoma	0.024, 0.4603, 0.3467, 0.0761, 0.0929	0
arjun	0.2057, 0.2178, 0.2445, 0.1066, 0.2254	0
hamid	0.1323, 0.2918, 0.2979, 0.114, 0.164	0
nikhil	0.1917, 0.0321, 0.1586, 0.3633, 0.2544	0
chandan	0.2379, 0.0949, 0.2591, 0.3375, 0.0706	1
stan_vj	0.0601, 0.1588, 0.1339, 0.1934, 0.4537	0
sagar	0.3777, 0.2044, 0.1312, 0.1328, 0.1539	0
trump	0.2716, 0.3353, 0.0194, 0.2713, 0.1024	0

system. The number of likes for each tweet was one of the important parameters to be set as an input to the inference system as it shows the amount of interest and popularity of each tweet. The parameter is not individually taken as an input to the inference system but as a number in a specific ratio. The above graph thus helps to analyze this input parameter much more accurately and efficiently.

Figure 11 b) shows the relation between the tweet and the number of retweets on that tweet. A retweet is a re-posting of a Tweet. Twitter's retweet feature helps a person to quickly share that tweet with all the followers one has. Hence, it forms another most important feature that helps in the selection of the best tweets from the ones obtained.

Figure 11 c) shows a relation between the tweet and the number of followers of the user who tweeted the tweet. The follower count helps to predict the popularity of a particular tweet as it helps to determine the reach of a particular tweet. However, it might not always be true that a user with a high number of followers always gets the maximum retweets or likes. Hence, we do not explicitly take this as input but a number to be used in various ratios.

Figure 11. Ratio of a) likes/time b) likes/follower c) retweet/follower

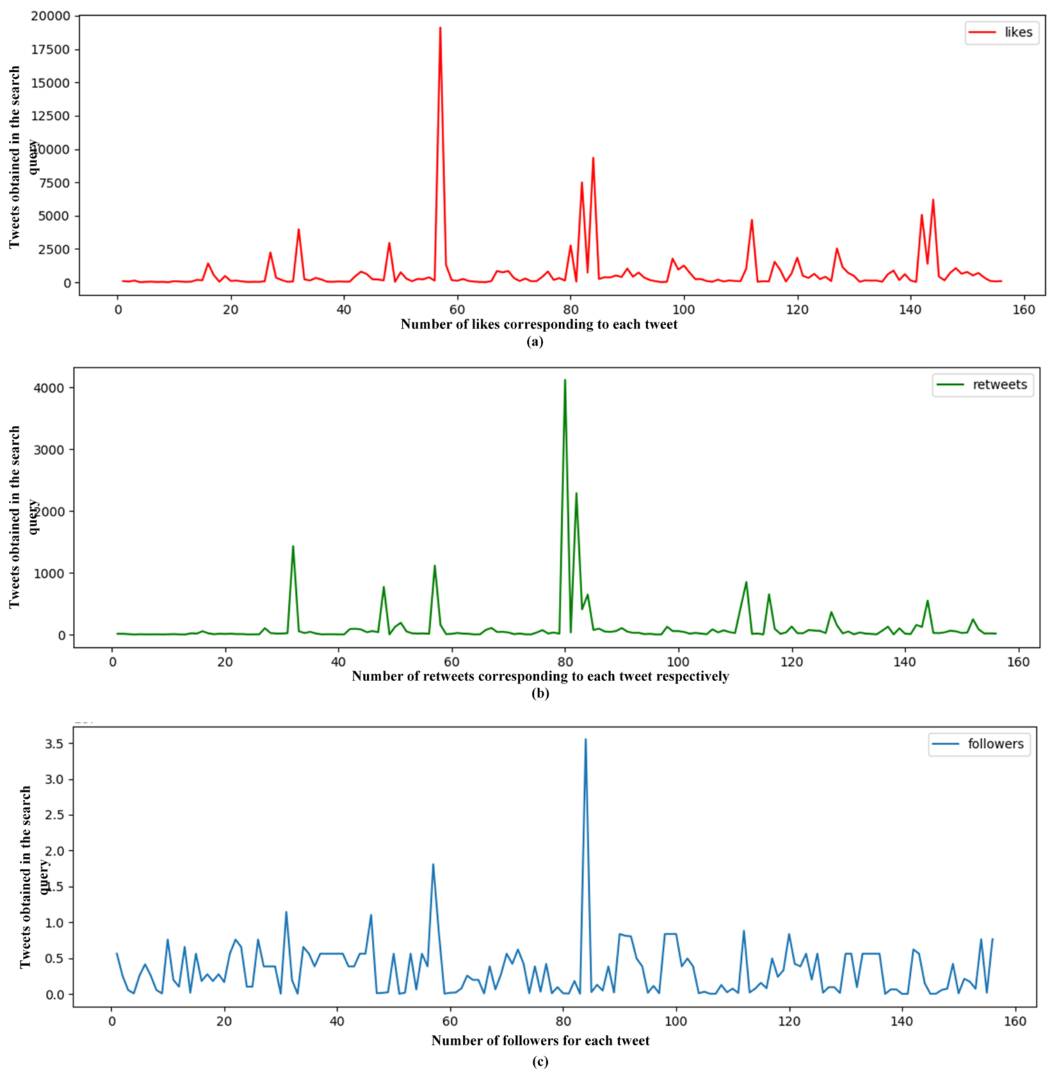


Figure 12 a) shows the relation between the tweet and the ratio of likes/time on that tweet. The PNTRS user must be provided with the best and the latest tweets every time, and hence the ratio of likes/time is used. The lesser the time difference of a tweet being posted and received in the search query, i.e., the more latest the tweet, the better the ratio. The tweets with the highest peaks have a greater chance of being selected through the inference system.

Figure 12 b) shows the relation between the tweet and the ratio of likes/follower. This ratio helps to select the best tweets from the ones obtained through a search query. The graphs' peaks help to analyze and determine the tweets that need to be selected through this parameter. The higher the rise, the better the tweet.

Figure 12. For each tweet a) No. of likes b) no. of retweet c) no. of followers

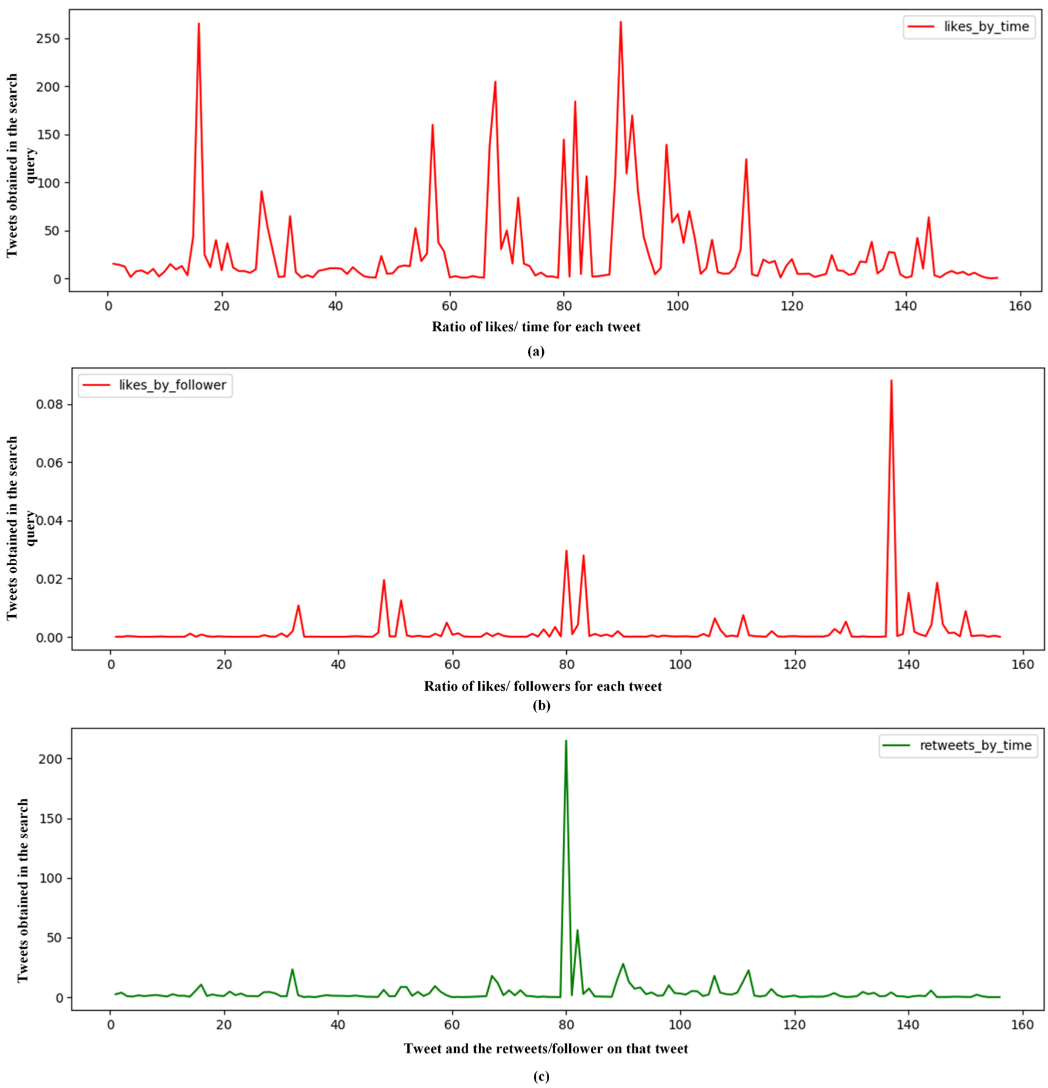


Figure 12 c) shows the relation between the tweet and the retweets/follower on that tweet. The variation in the graph helps to determine the best possible tweets one can obtain through this parameter. The tweets around the number 79-82 show a high peak, indicating a high chance of being selected through the inference system.

Sample results of the PTRS is shown in Table 4. For display purpose a pseudo tweet id is used in table as actual tweet id is 64 bit. The actual rating given by FIS is in range (1 to 25). This is further normalized to the scale of 1 to 5.

In order to check the satisfaction level of user they are asked to provide the feedback on news and tweet recommendation on a scale of 1-10. Eight users gave the rating above 7 and the average rating given by them is 7.9.

CONCLUSION

The PNTRS has been built with the aim of recommending personalized news to the user and, based on this personalized news, it recommends the personalized tweets to the user. The user is provided with the latest news articles of his/ her preferences and is imparted with the knowledge of discussions, viewpoints, and opinions of different people on the same by providing the tweets based on the recommended news articles. The feedback obtained from the initial set of registered users of PNTRS is 7.9 on a scale of 10 and it is quite motivating.

Table 4. Sample results of tweet recommendation

Tweet id	Likes	Retweets	Follower (s)	Likes/ Time	Retweet/ Times	Likes/ Followers	Retweet/ Followers	Occur-rence	Rating
39	51	15	1132792	13.75	4.04	4.5E-05	1.3E-05	1	12.45
33	18	6	6538107	2.65	0.88	2.8E-06	9.2E-07	5	12.38
44	1037	430	57500	13.95	5.79	1.8E-02	7.5E-03	1	12.34
2	31	17	2544872	7.48	4.10	1.2E-05	6.7E-06	1	11.06
95	17	5	4132505	4.97	1.46	4.1E-06	1.2E-06	1	9.94
40	413	206	22688	2.82	1.41	1.8E-02	9.1E-03	1	9.88
89	7	5	1976656	1.90	1.36	3.5E-06	2.5E-06	1	9.83
4	21	5	2947921	5.32	1.27	7.1E-06	1.7E-06	1	9.71
6	9	5	1976656	2.19	1.22	4.6E-06	2.5E-06	1	9.64
34	25	5	11407434	6.02	1.20	2.2E-06	4.4E-07	1	9.62
52	35	4	7965180	8.27	0.94	4.4E-06	5.0E-07	1	9.42
57	272	48	447369	4.81	0.85	6.1E-04	1.1E-04	1	8.88
8	10	5	1976656	1.55	0.77	5.1E-06	2.5E-06	1	8.66
39	27	6	741422	2.48	0.55	3.6E-05	8.1E-06	1	7.86
10	93	43	86732	0.94	0.43	1.1E-03	5.0E-04	1	7.32
30	116	60	10392	0.80	0.42	1.1E-02	5.8E-03	1	7.24
90	38	22	11110	0.26	0.15	3.4E-03	2.0E-03	1	5.62

In the future, better and larger dataset may be used to evaluate and improve the results obtained after training the model. Further, to improve the accuracy, RNN and CNN can be applied to recommend the personalized news articles more efficiently.

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