A News Recommender System: Implementation and Analysis

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In the past few years, the need of prediction has been increased rapidly. Predicting the purchase, reading of news, buying food items are few popular interests of researchers and marketing people as well. Newspapers are quite essential to urge information concerning recent activity and general awareness for all age group. Varied solutions are being developed to convert paper News system to digital news and it has become a standard for all news company. Recommendation system has been proposed and developed for suggestion to the user. Researchers have developed many algorithms for developing the recommendation system. Each approach has its pros and cons. In this paper, we have studied different approaches for news recommendation systems and developed a content-based filtering model for recommending the news articles to the user. The articles with more euclidean similarity have higher chances of suggesting to the user.

Keywords: Recommender system, Content based filtering, Collaborative Filtering, News Recommendation.

1 Introduction

In this era of rapid growing social media interactions and communication technologies, Internet plays a vital role and has become an integral source of news due to its dedicated availability, quick updates and access. Social media sites such as Facebook, Twitter, Instagram, Snapchat generate enormous amount of data. Moreover, this data is also affecting the life of its users in good as well as in bad ways.

2023. In Saroj Hiranwal & Garima Mathur (eds.), *Artificial Intelligence and Communication Technologies*, 245–261. Computing & Intelligent Systems, SCRS, India. https://doi.org/10.52458/978-81-955020-5-9-26

Figure 1: Different categories of news

It is very cumbersome for the user to identify which data is relevant and true also. Recommender systems are proposed and developed to address the above problem [1], [2], reported by Pew research center in 2018, approximately, 93% people in US prefer reading the news online through social media, apps, digital newspaper etc [3]. As online news is preferred more, there should be such a system providing the news based on user's behaviour, their choices, previous search etc. As a result, tools and techniques like recommendation systems are needed to give news updates that are relevant to user's knowledge demands. Nowadays, many news channels and agencies provide access to news readers to browse latest news online. Due to increasing demand of the user and heavy traffic to the news websites, online news outlets are adopting systems, recommending related news and improving user experience [4]. In the literature, researchers have worked on recommending news by proposing and implementing different algorithms. There are many categories of news (refer Fig. 1) and these categories keep on growing with this dynamically changing world and the news recommender systems also are recommending news based upon these categories.

News recommender system is a growing interest of researchers as its benefits, challenges, future aspects have been discussed in surveys [1], [2], [5]. In this paper, the authors studied different techniques for recommending news article to the user and implemented content-based filtering method word2vec for recommending news to the user.

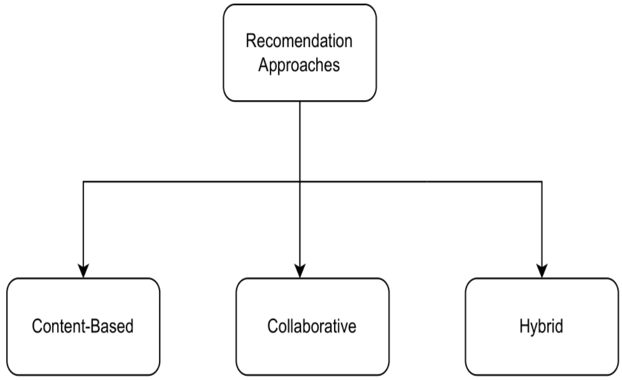

Figure 2: Different approaches applicable for recommender system

2 Background

In this section, we have detailed about news recommender systems and its different approaches. Literature in the area is also reviewed.

2.1 Recommender System and Approaches

The recommender system works based on few traditional algorithms and these algorithms are: collaborative filtering (CF), content-based filtering (CBF), knowledge based (KB) and hybrid based approach (HB) (refer Fig. 2).

2.1.1 Content-based filtering:

Content based algorithm is one of the most used by the researchers. It makes recommendation based on user's previous activity. It creates user profile based on user actions, ratings, purchasing habits, downloads, web searchers and product link click. It uses keywords and attributes that are assigned to objects of dataset and match them with the created user profile. Content-based filtering finds similarities in products, services, or content features, as well as information accumulated regarding the user choices to make recommendations. Content based filtering is further classified into various techniques: vectorization, Bag of words, TF-IDF (Term Frequency (TF) - Inverse Dense Frequency (IDF)), Word Embedding (Word2Vec) [9], [2], [10], [9].

These recommendations are always relevant to the user as predictions are based on user profile. This type of recommendations systems are also very easy to create and maintain.

2.1.2 Collaborative filtering:

Collaborative filtering (CF) offers recommendations to a specific user based on the preferences of other users. It is the most popular recommendation approach which is based on estimated guesses. CF uses data in terms of standards, history and interaction. This filtering requires items set based on the user's previous preferences. This approach provides three ways for recommendation: user-to user based on user to user similarity, item-to item based item wise similarity, factor based on user-item preferences. Users are classified into clusters and each cluster has similar users and recommend each cluster's users based on the preferences. For collaborative filtering, clustering, KNN, matrix factorization, link analysis and decision tree techniques are used [1].

2.1.3 Hybrid Filtering:

In hybrid approach, both Collaborative Filtering and Content-based Filtering are combined [7], [8] to learn the similarity between the user-item pairs that allows simultaneous generalization across either user or item dimensions. This approach would do well when the user item rating matrix is dense (e.g. 6% as reported by [8]). However in most current recommender system settings, the data are rather sparse, which would make this method fail.

2.2 Literature Review

As per the surveys [13], [1], [2], different approaches and dataset have been used for recommender systems. In this section, the authors have reviewed the literature in the area as listed in Table 1.

In 2009, Park et al. [19] developed a newscube model to handle the media bias. It recommends the user multiple viewpoints on a news. Newscube applies aspect level browsing that suggests the news reader different news with several aspects. The model incorporates content based filtering techniques. Later, CBF was used by various researchers [20], [21], [23],

Oh et. al. [25] worked upon extraction technique to capture the user preference by exploring the important keywords from the news articles read by the users. They used term frequency and Inversed Document Frequency (TF-IDF) for keyword classification.

In 2014, [24] implemented CBF technique for news recommendation on twitter and facebook data in a cold-start scenario.

Content based filtering with collaborative filtering is also used in hybrid mode by researchers in [31], [26].

Table 1: Related work in the area of news recommender system

Author	Year	Dataset	Algorithm
Park et al. [19]	2009	Google News	CBF
De Francisci Morakas et al. [20]	2012	Twitter Yahoo	CBF
Agrawal et al. [21]	2013	RSS News Feed	CBF
Adnan et al. [22]	2014	Bdnews24.com	Fuzzy Logic
Gu et al. [23]	2014	News.sina.com	CBF
Trevisiol et al. [24]	2014	Facebook, Twitter	CBF
Oh et al. [25]	2014	Korean news	CBF
Li et al. [30]	2014	Wikidata, Weibo	CBF,CF
Muralidhar et al. [26]	2015	Washington Post	CBF,CF
Lu et al. [31]	2015	Bing news	CBF, CF
Jenders et al. [27]	2015	New York Times	CBF
Viana and Soares [28]	2016	-	CBF, CF
Lin et al. [29]	2017	News.sohu.com	CBF,CF

* CF: Collaborative Filtering, CBF: Content Based Filtering

2.3 Challenges

Various challenges have been faced by the researchers as found in [14], [1], [11], [2], [12], [13]. Few challenges are listed below.

- Cold start problem is faced when recommender system is built based on collaborative filtering. Collaborative filtering requires user feedback, number of clicks, ratings, feedbacks, however, this information is not available when a new user joins the system [15], [16].

- Feedback from the user may be related to how much user is satisfied with the product, news etc. Sometimes, user provide the feedback without any interest or lack on time, that may affect the accuracy of recommender systems [16].

- Interests and likes of user changes with time, that is also a challenge to the recommender system [14].

- Another challenge is providing the recent events information to the user. However, sometimes, old articles are also important to the user based on context of current news [14], [16].
- News are updated every single minute, news are changing rapidly. It is also a challenge to the recommender system [17].

3 Working of Recommender System

Recommender systems are used in almost everywhere nowadays. The importance of the system is accuracy of prediction and suggestion to the user. In this section, we present how these system work and make predictions 3.

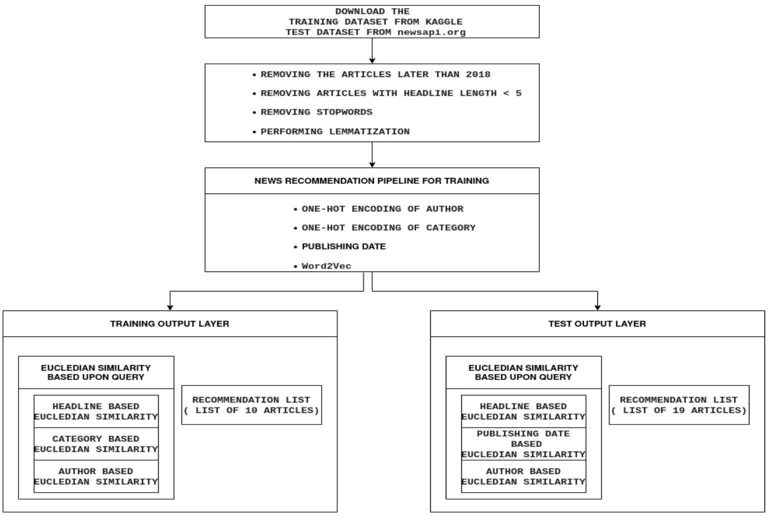

Figure 3: Working model of news recommender system

Initially, developer needs to select the dataset. Dataset should be large enough to make the right suggestion. For this, we need two datasets, one for training the model and another for testing the accuracy of model. In this work, we downloaded the training dataset from Kaggle and the test dataset from newsapi.org (an API service to obtain latest news for development purposes).

From the training dataset, we removed the articles older than 2018 followed by which we remove the articles which have headlines with length less than 5 words. This is done so as to ensure the avoidance of bias caused because of fewer words in the headline.

Secondly, we remove the stopwords from our headline text because stop words are not that much helpful in analysis, also including them consumes much time during processing so better remove them.

In the next step, we apply lemmatization upon the words in our headlines. Lemmatization helps us find the base form(lemma) of each word and helps us to consider different inflections of a word same as the lemma. Thirdly, we encode our dataset's author, category using one-hot encoding and then we apply word embedding technique (Word2Vec). It is based on content based filtering approach [18].

The model is then trained and predictions are made upon test dataset. To make the recommendations, euclidean similarity is calculated and higher similarity indices are preferred for suggestion.

The library we used above for as to remove stopwords, for lemmatization and creating word embeddings are discussed as below :

3.1 Lemmatization

Lemmatization is one of the most common, text pre-processing technique we use in Natural Language Processing (NLP). In lemmatization, we try to reduce a given word to its root word. In a lemmatization algorithm, for eg. Given a word "goodness" realises that the given word's base word is "good" i.e. it is derived from the word "good".

3.2 StopWords Removal

The words which generally are removed before we processing a natural language are called as stopwords. Stopwords are the most common words used in any language (eg. Articles, pronouns, prepositions, conjunctions, etc) but do not add much information to the text being analysed. Some examples of stop words in English language are "the", "a", "an", "what", etc. Stop words are abundantly available in any language. Removing these words help us get rid of low-level information from text and gives more focus to the important content. Removing such words does not result into any negative effects on the model we wish to train for our task. Natural Language Toolkit (NLTK) is an amazing library for working with natural language and te library is imported to remove stop words.

3.3 Word2Vec

Word2vec technique is for natural language processing and was released in year 2013. This algorithm reads the words and learns the association between words using neural network model. After the training of model, it can detect words that are synonymous to the queried word or suggest some additional words for incomplete or partially complete sentences. As it goes by the name, word2vec technique represents every distinct word as real number, and these numbers are generally stored in a vector hence it is named as Word2Vec. The comparison between the real number stored in different vectors corresponding different words (e.g., using cosine similarity) indicate the extent of semantic similarity between the represented words. The vector is also named word embeddings.

4 Experimenal Setup

4.1 Data Set

Data set plays an important role in recommender systems. Different datasets are being used by the researchers as found in literature review (Table 1). Data set description is illustrated in Figure 4 The information regarding our data set is demonstrated in Figure 5, 6.

Training Dataset description:

No. of articles: 200853

Attributes:
'category', 'headline', 'authors', 'link','short_description', 'date'

Categories: 'POLITICS', 'ENTERTAINMENT', 'WORLD NEWS', 'QUEER VOICES', 'COMEDY',
'BLACK VOICES', 'SPORTS', 'MEDIA', 'WOMEN', 'WEIRD NEWS', 'CRIME',
'BUSINESS', 'LATINO VOICES', 'IMPACT', 'TRAVEL', 'RELIGION', 'TEH',
'SCIENCE', 'STYLE', 'PARENTS', 'EDUCATION', 'GREEN', 'HEALTHY LIVING',
'ARTS & CULTURE', 'TASTE', 'COLLEGE'

Article Source: Kaggle

Test Dataset Description:

No. of articles: 20

Attributes:
'source', 'author', 'title', 'description', 'url', 'urlToImage', 'publishedAt', 'content'

Categories: 'POLITICS', 'ENTERTAINMENT', 'WORLD NEWS', 'QUEER VOICES",COMEDY',
'BLACK VOICES', 'SPORTS', 'MEDIA', 'WOMEN', 'WEIRD NEWS', 'CRIME',
'BUSINESS', 'LATINO VOICES', 'IMPACT', 'TRAVEL', 'RELIGION', 'TECH',
'SCIENCE', 'STYLE', 'PARENTS', 'EDUCATION', 'GREEN', 'HEALTHY LIVING',
'ARTS & CULTURE', 'TASTE', 'COLLEGE'

Article Source: newsapi.org

Figure 4: Data set desciption

Figure 5: (a) Month wise articles in data set (b) Probability of articles based on headline

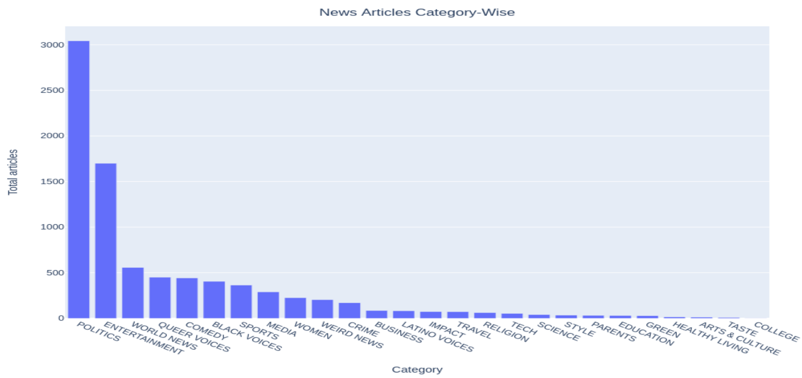

Figure 6: Category wise total articles found in dataset

4.2 IDE and Framework

To implement our system, we use Python and Jupyter Notebook. It is a web application used for creating and sharing of computation documents. It offers its user a simple and document centric experience. Jupyter could be used with around 40 programming languages in including Julia, R and Python.

5 Results

We implemented the recommendation system in Python, Jupyter Notebook. Training data set and test data set (explained in Section 4.1) are used for recommendatiing the articles. We have discussed few results below for the article queried. Figure 7 shows the query raised for training data set and corresponding results are displayed in Table 2. Figure 8 shows the query raised for test data set and its results are listed in Table 3 (see last page). The similarity measure metric used for comparing the articles is as follow

5.1 Similarity measures used:

5.1.1 Cosine Similarity

Cosine similarity metric helps to determine of how similar a data object is to other without considering the size of the objects. Similarity between two sentences of equal/unequal length can be calculated in python using cosine similarity. In cosine similarity, the data objects in any dataset are treated as vector. The advantages of using cosine similarity are:

The cosine similarity become useful because even if there exists two data objects far apart by the Euclidean distance because of their size, they still could have a smaller angle between them. Smaller is the angle, higher becomes the similarity between the data objects.

When we plot the data objects on a multi-dimensional space, cosine similarity considers the orientation or say the angle between the data objects and not the magnitude.

5.1.2 Eucledian Distance

Euclidean distance is a technique used to find the distance/dissimilarity among objects. The Euclidean distance between any two points is the length of a line segment between those points. It can be computed using the cartesian coordinates of the points with the help of the pythagorean theorem therefore occasionally being called the Pythagorean distance. Here the distance between the articles by plotting the articles in english vocabulary dimension space and finding the length of the line segment joining these articles in that space.

```
============================== Queried article(Training Data Set)============================
headline :  Universities Tell Applicants That Protesting Gun Violence Won't Affect Admissions
Categoty :  EDUCATION
Authors :  Carla Herreria
```

Figure 7: Query article for training data set

The model gives vector representation for every word but we calculate our distance between headlines so we try to obtain vector representation for each

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======================= Queried article(Test dataset)=========================
headline :  Samsung Galaxy F23 5G brings Snapchat filters in camera app! Know how to use it
Authors :  HT Tech
Day and month :  Sat_Apr
```

Figure 8: Query article for test data set

word of each headline. To build a robust recommender system, we need to consider multiple attributes at the same time. Based on our use case, we can decide weights for each of our attribute.

Considering this, we provide our model with combinations of different attributes for article similarity. Sometimes as per the user requirements, we might need to give more preference to articles from the same author or category or mainly publisihing day for say breaking news . In these cases, we can assign more weight to the category, author or publishing day while recommending. Higher the weight, larger the importance that attribute will reflect on our recommendation. Similarly, less weight leads to lesser importance to that particular feature. Our pipeline takes three extra weigths as arguments w1 and w2 as weights corresponding to headline and category. It is always good to pass the weights in a range of 0 and 1, where a value close to 1 indicates high weight whereas value if close to 0 indicates low weight. Note that publishing day we've not considered here but will do in test data.

We encode our author attribute through one-hot encoding. Our pipeline takes one extra weight argument w3 for our author attribute. From the results, we observe that our recommended articles are from same author as of in our query article's author. This is due to high weightage given to w3. We can see the results are mainly from the author "Carla Herreria" not just because of high weights given to attribute author but because also our model tried to catch the context of the headlines words and the writer's inherent choice of words as we can see we get recommended articles from different categories written by the same author.

For test data set, we can see the prediction here (refer Figure 8, Table 3) is upon the 10 test articles of the 20 articles from newsapi.org. We can see that as our queried article is "Samsung Galaxy F23 5G brings Snapchat filters in camera app! Know how to use it", our predictions here involve the articles with other technical stuff like mobile phones and metaverse technologies, etc. Also we get some out of context recommendations like articles related to coronavirus and this happens just because of very limitied size of our test set. Therefore the best related articles get recommended on top and then others with comparatively larger distance.

Table 2: Recommended articles for query on training data set

Headline	Weighted ES	Word2Vec ES	Category ES	Authors ES	Category
MSU Students Wear Teal To Show Support For Survivors Of Larry Nassar's Abuse	1.10	1.17	2.41	1.0	SPORTS
Steven Mnuchin Doesn't Want People To See Video Of His Heckled UCLA Talk	1.11	1.18	2.41	1.0	POLITICS
Sen. Marco Rubio Tells Students He Does Not Agree With The March For Our Lives	1.12	1.20	2.41	1.0	POLITICS
NBA Star Reveals Struggle With Panic Attacks And How Men 'Suffer Silently'	1.12	1.22	2.41	1.0	SPORTS
Trustee Defends MSU President, Dismissing Sex Abuse Reports As 'Nassar Thing'	1.13	1.23	2.41	1	SPORTS
Howard Students Take Over Building To Protest University Embezzlement Scandal	1.14	1.23	2.41	1	BLACK VOICES
Dylann Roof's Sister Accused Of Having Weapons At School During National Walkouts	1.14	1.24	2.41	1	CRIME
Democrats Flood McCabe With Federal Job Offers So He Can Access His Pension	1.14	1.24	2.41	1	POLITICS
Prominent LGBTQ Lawyer Sets Self On Fire In 'Protest Suicide' Of Climate Change	1.15	1.25	2.41	1	QUEER VOICES

* ES: Euclidean Similarity

Since we perform our recommendation based on distance hence the smaller the distance between two articles, more is the similarity and hence we recommend those article above the articles that have comparatively larger distance. The distance here is calculated using the Eucledian Similarity and the articles with lesser distance are recommended above the articles with comparatively larger distance from the queried article.

6 Conclusion

Recommender systems have become very important and have made a lot of progress in recent years especially in the years when the users want to get recommendation upon anything that can be consumed. Also, a plenty of techniques are already developed to boost the quality of recommendations made by the recommender systems. The issue arises because of our dynamically changing world where every minutes google has to recommend a whole new set of recommendations to stay at par with the competetiors. Hence , In most cases we need to design new techniques to boost the accuracy of our recommendations. Planned system will not solely observe the content of news on the preference of the user or based on quality, rather conjointly refine the articles on priority and upon the basis of the impact the recommendations create. Planned systems can help into refining common and effective content of news or other domains as well and stay in step with user needs.

The future scope of our proposed solution is that it can be tested and expanded with other news dataset such TOI or the hindu and other news domains. It can be applied to some specific news domains like for tech we can scrape the news from Beebom or GSMarena. In this paper, we focussed upon how to build an entire news recommender system from scratch using the present techniques and solving the issues that developers face in the current scenario in this dynamically changing world of news recommender systems.

Table 3: Recommended articles for query on test data set

Headline	Weighted ES	Word2Vec ES	Author ES	Publish Date ES	Authors
Redmi 7 price cut on Amazon makes it super affordable	0.86	0.73	1.00	1	HT Tech
New Metaverse technology allows you to kiss and feel	0.91	0.70	2.41	1	WION Web Team
Coronavirus News Live Updates: 3,688 fresh Covid-19 cases, slightly higher than yesterday; 50 deaths in 24 hours	0.95	0.77	2.41	1	Express Web Desk
PSY's much-awaited That That feat BTS' Suga becomes a phenomenon, tops charts in 73 countries. Watch	0.95	0.78	2.41	1	Entertainment Desk
Boris Becker JAILED: Shamed Wimbledon champion looks shocked as he's led from dock	0.99	0.86	2.41	1	Archie Griggs
Putin's invasion of Ukraine is of 'most depraved sort' -Pentagon	0.99	0.86	2.41	1	Reuters
LIVE AFL: 'Superb' Docker's epic performance; 'worried' Cats' 52-min drought	1.01	0.88	2.41	1	Ben Cotton
GT vs RCB Dream11 Prediction, Fantasy Cricket Tips, Dream11 Team, Playing XI, Pitch Report, Injury Update- Tata IPL 2022	1.04	0.95	2.41	1	More by Vicky Singh
MP Neil Parish says he may have opened porn in Commons by mistake	1.05	0.97	2.41	1	Alix Culbertson
Thousands face losing summer holidays as Passport Office delays continue	1.11	1.08	2.41	1	Anna Tims

* ES: Euclidean Similarity

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