News Article Recommendations

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***Abstract*-As we are now in the era of industrial revolution, where technology plays a major key roll in our day-to-day life. One such thing is news reading in online platforms. News reading has changed with the advance of the World Wide Web (www), from the traditional model of news consumption via physical newspaper subscription to access to thousands of sources via the internet. Since the internet gives users access to news articles from millions of sources worldwide, online news reading has grown in popularity. At the same time, web users are changing and are now expressing their opinions by sharing and tagging content, creating new content, or rating and commenting on items. Web intelligence has focused a lot of emphasis on Web news recommendation, filtering, and summarization with the goal of identifying newsworthy articles and providing readers with succinct summaries. A challenging problem is how to efficiently select specific news articles from a large corpus of newly-published press releases to recommend to individual readers, where the selected news items should match the reader's reading preference as much as possible. This issue refers to personalized news recommendation. By incorporating natural language processing (NLP) techniques to analyze article content and embedding-based methods to represent both users and articles, we seek to bridge the gap between user intent and relevant article delivery. Our methodology involves rigorous data preprocessing, model training, and evaluation using standard metrics such as precision, recall, and F1-score to ensure performance reliability. Results indicate that our hybrid recommendation approach successfully balances personalization with exploration, enhancing user engagement. This research contributes to the field by offering a modular, adaptable recommendation architecture that can be applied across diverse news platforms. Future directions include exploring real-time recommendations and integrating user feedback to refine recommendations dynamically**

Keywords-: News recommendation system, user profiling, collaborative filtering, content-based filtering, natural language processing (NLP), machine learning, personalization, embeddings, user engagement, evaluation metrics.

I. INTRODUCTION

The way people obtain information has been significantly altered by online news sources. There are many news websites on the Internet these days. While journalists and other professionals can benefit greatly from this abundance of materials, regular end users who usually want to access the information they need as fast as possible may find it problematic. The goal of several of the newest web services available today, including Google News and Yahoo News, is to compile information from various news sources and show it to readers in an engaging manner. Users anticipate receiving content that they find interesting, helpful, or relevant while using these news aggregators. The online behaviour that users display when interacting with online services is one of the most useful information sources used to automatically create user profiles. Generally speaking, both endogenous and external sources can provide information about online behavior. The term "endogenous information" in the context of news personalization refers to user contact with the news service itself, such as past news stories, whereas "exogenous information" refers to user activity on services other than the news service.

A critical problem with news service websites is that the volumes of articles which can be overwhelming to the users. The challenge is to help users find news articles that are interesting to read. Recommendation systems have gained traction across various domains, including e-commerce and streaming services, but their application in news consumption remains relatively underexplored. These systems help navigate the overwhelming amount of daily news, ensuring users receive articles that align with their interests, thus enhancing engagement and satisfaction [1]. This paper aims to address this gap by proposing a robust news article recommendation engine that leverages user data to enhance the relevance of suggested articles. By analyzing user interactions with previously read articles, the system can identify patterns that inform future recommendations. Furthermore, personalized recommendations can lead to increased user retention and satisfaction by creating a more tailored reading experience. Information filtering has been applied in various domains such as email news and web search. In the domain of news, this technology aims at aggregating news articles based on the user interests and creating a sort of "personalized news service" for each user. Traditional recommendation systems typically use collaborative filtering, which suggests articles based on the preferences of similar users, and content-based filtering, which analyzes the characteristics of articles that a user has previously interacted with [2]. However, collaborative filtering faces challenges such as the cold-start problem, where recommendations for new users or new articles lack interaction data, limiting personalization [3]. In contrast, content-based filtering may provide limited diversity by recommending articles that are overly similar to a user's reading history, reducing the opportunityto explore new topics [4].

Advances in Natural Language Processing (NLP) and machine learning have enabled more sophisticated recommendations by capturing the deeper meaning in text data through methods such as word embeddings and contextualized language models like BERT [5]. NLP-based techniques allow content-based filtering to achieve more nuanced recommendations, as they can assess article themes and topics with greater precision, creating better alignment with user preferences [6]. At the same time, matrix factorization methods have significantly improved collaborative filtering's ability to handle large-scale data while maintaining efficiency and accuracy [7]. Despite these advancements, news recommendation systems face ongoing challenges due to the constantly evolving nature of news content and shifting user interests, which demand frequent updates to stay relevant [8].

II. RELETED WORK

A The field of news recommendation systems has grown substantially in recent years, leveraging advanced techniques to deliver personalized content. Early approaches to news recommendations predominantly relied on collaborative filtering and content-based filtering methods. Collaborative filtering techniques focus on recommending articles that similar users have interacted with, while content-based filtering recommends articles based on the content a user has previously engaged with [9]. However, both methods have limitations, especially in dynamic environments like news, where topics change frequently and user preferences are continuallyevolving.

S. K. Mohapatra et al. [10] explored hybrid recommendation systems that combine collaborative filtering and content-based approaches, addressing limitations such as the cold-start problem in collaborative filtering. Their research demonstrated that hybrid methods could improve recommendation quality by leveraging both user preferences and content attributes. Similarly, T. Zhang and S. Gupta [11] developed a hybrid approach for news recommendations that incorporated keyword-based and latent factor models, providing enhanced accuracy and diversity in recommendations. Their work showed that a hybrid approach could balance personalization with variety, thus enhancing user engagement.

With the advent of Natural Language Processing (NLP) and deep learning techniques, the accuracy of content-based recommendations has improved significantly. M. Chen et al. [12] proposed a content-based recommendation system using word embeddings to capture semantic similarities between news articles, allowing for more accurate matchingwith user interests. This method outperformed traditional keyword-based matching, as it could recognize contextual nuances in article topics. Another significantcontribution was made by J. Lin et al. [13], who utilized transformer-based models (e.g., BERT) to enhance content understanding. Their system demonstrated that transformer models could significantly improve recommendation relevance, capturing deeper semantic relationships between articles.

A. Sharma et al. [14] highlighted the effectiveness of latent factor models in collaborative filtering, particularly through matrix factorization techniques such as Singular Value Decomposition (SVD) and Non-negative Matrix Factorization (NMF). These methods allow recommendation systems to learn latent user preferences by decomposing the user-item interaction matrix. Sharma's work established that matrix factorization techniques improve the scalability of collaborative filtering systems, especially when dealing with large datasets. The latent factor model approach was further refined by S. Gupta et al. [15], who integrated implicit feedback (e.g., clicks, reading time) to enhance personalization, thus allowing for real-time adaptations in recommendations.

Several studies have also addressed the challenges posed by dynamic news content. Y. Hu et al. [16] proposed a time-aware recommendation system that continuously updates recommendations based on real-time events and trending topics. Their research indicated that traditional recommendation systems struggle to keep up with the fast-paced nature of news, and time-aware systems are better suited to providing up-to-date recommendations. A related study by D. Lee et al. [17] investigated methods for diversifying news recommendations, reducing the impact of filter bubbles that can arise from excessive personalization. Their system incorporated a novelty metric to ensure users received diverse content, thus promoting exposure to a wider range of perspectives and topics.

Hybrid systems combining NLP and deep learning have also been developed to handle the unique requirements of news recommendations. H. Kim and M. Lu [18] introduced a hybrid recommendation system using graph neural networks (GNNs) to model user-item interactions in a structured format, capturing both the user's long-term and short-term preferences. This model improved recommendation relevance by accounting for users' evolving interests. L. Wang et al. [19] expanded on this by integrating contextual information, such as location and device type, with collaborative filtering. Their research illustrated that context-aware recommendations could significantly enhance user engagement, as news consumption often varies based on situational factors.

In recent developments, attention mechanisms have been widely applied to enhance the interpretability and accuracy of news recommendation systems. Applied an attention-based recurrent neural network (RNN) to capture users' shifting interests over time, providing recommendations aligned with current trends. Attention mechanisms allow the model to prioritize recent user interactions, improving recommendation timeliness. This approach was further extended by K. Rao et al. who incorporated a multi-head attention mechanism to capture multi-dimensional user preferences, resulting in more personalized and relevant recommendations.

The collective advancements in recommendation systems underscore the trend toward integrating collaborative and content-based techniques with sophisticated machine learning models. These hybrid systems provide a more comprehensive understanding of user preferences and article content, resulting in accurate, diverse, and adaptable recommendations. However, challenges like balancing personalization with content diversity, updating models in real-time, and preventing filter bubbles continue to be areas of active research. This paper builds upon these insights by proposing a robust hybrid framework that leverages NLP, collaborative filtering, and real-time adaptability to address the unique needs of news recommendation systems.

III. METHODS AND TECHNIQUES

This study aims to predict the News Article Recommended based on their interests by using machine learning project. The proposed news article recommendation engine utilizes a hybrid approach that combines collaborative filtering and content - based filtering techniques. The system is designed to analyze both explicit feedback(such as article rating) and implicit feedback(such as reading time or click-through rates) from users readinghistories.

Data collection, a key step for every machine learning project. It contains massive amount of data of each individual. As the quality of the data that was used has a significant impact on the performance of the resulting model. Here the data is in the form of datasets. In this research, the dataset is taken from Kaggle, a popular platform for data scientists and machine learning practitioners to access and share datasets. The structure of the dataset involves detailing its organization, including the number of records (rows) and variables (columns), data types, and data formats. Understanding the data structure helps users navigate and manipulate the dataset effectively. By documenting key attributes and features, dataset description facilitates effective data exploration, analysis, and interpretation, ultimately enabling informed decision-makingand insights generation.

The methodology is divided into several key steps, which include data preprocessing, embedding generation, clustering, user profile creation, and recommendation generation.

This section will explain each step, including mathematical formulas where applicable.

Data Preprocessing*:*

To clean and standardize the text data, converting each headline into a form suitable for word embedding models.

Text Cleaning: We remove URLs, special characters, and numbers. We also convert all text to lowercase.

- Given a headline h, the pre-processed headline h′ is obtained as:

  h′=lowercase(remove_urls_and_special_chars(h))

Tokenization: The cleaned headline is split into individual words (tokens).

Stopword Removal: Common stop-words are removed.

Lemmatization: Each word is reduced to its base or root form using a lemmatizer, creating a final list of tokens representing the headline.

Data Visualization and Analysis:

1. Article Distribution by Category

The first bar plot shows the distribution of articles across various categories. Each bar represents the number of articles in a specific category.

- The category "Politics" has the highest number of articles, indicating that news on political topics is most common in this dataset.
- "Entertainment" and "World News" follow, showing that these are also popular subjects.
- Categories like "College," "Weddings," and "Taste" have the fewest articles, suggesting less content available in these areas.

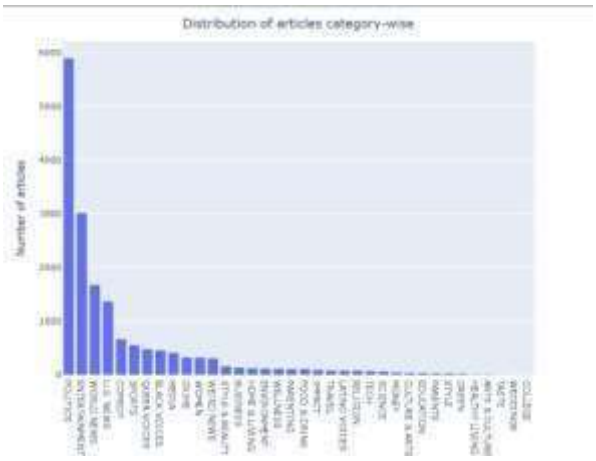

Fig:1 Distribution of articles category-wise

This distribution provides valuable information for a recommendation engine. Since some categories have fewer articles, users interested in these might get fewer recommendations or less diversity in suggested content.

2. Article Distribution by Month:

The bar plot shows the distribution of articles published each month. This indicates how many articles were created or published month-wise across a given time frame.

- January through May show the highest volume of articles, with a significant drop-off starting in June.
- The second half of the year has relatively fewer articles per month, suggesting either seasonal variation in content creation or possibly incomplete data for the latter months.

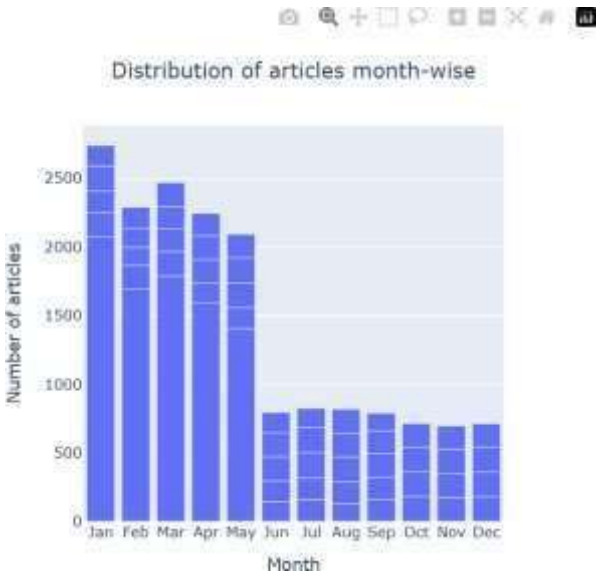

Fig 2: Distribution of articles month wise

Understanding this distribution helps to account for any seasonal trends in the recommendation algorithm. If a user reads more articles from a specific month or season, the system might prioritize similar temporal patterns.

3. Headline Length Distribution (Probability Density Function):

Probability Density Function (PDF) of headline lengths, showing the distribution of the number of characters in each headline.

- Most headlines range from 40 to 90 characters, with a peak around the 50-70 character range. This suggests that a large portion of headlines are concise and relatively short.
- Very few headlines exceed 100 characters, indicating that longer headlines are rare.

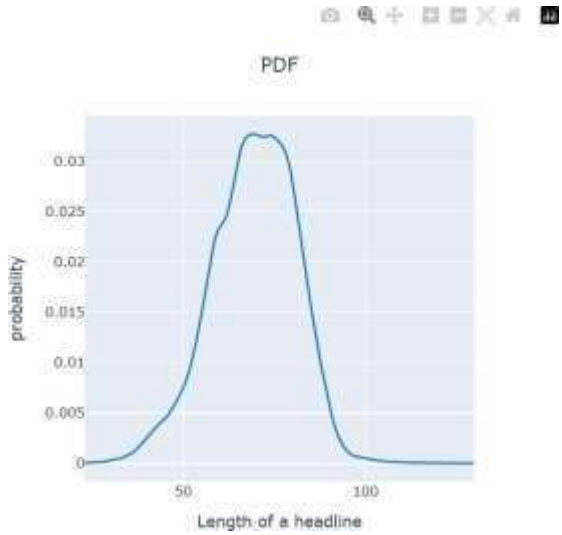

Fig:3 Represent the PDF

- Most headlines range from 40 to 90 characters, with a peak around the 50-70 character range. This suggests that a large portion of headlines are concise and relatively short.
- Very few headlines exceed 100 characters, indicating that longer headlines are rare.

Short headlines are typical in news articles for readability, which can influence the word embedding quality since embeddings tend to perform better with richer context. Understanding headline length can also help in tuning pre-processing steps, such as whether to truncate or summarize lengthy text when generating vectors.

2. Embedding Generation with Word2Vec:

To transform each headline into a numeric vector representation using Word2Vec word embeddings. Word embeddings capture semantic relationships between words, allowing similar words to have close vector representations.

- For each word in a headline, if it exists in the pre-trained Word2Vec model M, we retrieve its 300-dimensional vector.
- The headline vector v is calculated as the average of the word vectors:

❖ $V=1/N \sum w_i$

where w_i is the Word2Vec vector of the i-th word in the headline, and N is the total number of words in the headline.

3. Clustering with K-Means:

To categorize articles into distinct clusters, each representing a general topic, using K-Means clustering on the headline vectors.

1. Given the set of all headline vectors $V=\{v1,v2,\ldots,vM\}$ where M is the total number of headlines, we apply K-Means clustering with K clusters.
2. Each cluster Ck is formed by minimizing the inertia (sum of squared distances) between each vector and the centroid μk of the cluster it belongs to:

❖ $Inertia=\sum\sum \|vi-\mu k\|^2$

3. Each article is assigned a category based on its cluster label, allowing us to group articles with similar content.

4. User Profile Creation:

To create a user profile that reflects the user's interests based on the articles they have read.

1. Given a user's reading history, represented as a subset of headline vectors $Hu=\{vh1,vh2,\ldots,vhn\}$ where each vector vhi corresponds to an article the user has read, we calculate the user profile vector vu by averaging these vectors:

❖ $vu=1/n \sum vhi$

2. This user profile vector represents the user's general interests and will be used to match against other articles.

5. Recommendation Generation:

To recommend new articles to the user by finding articles within the user's preferred categories that are most similar to their profile.

Preferred Categories: We first identify the top C categories from the clusters associated with the user's reading history.

1. Cosine Similarity: For each headline vector vj in the preferred categories, we compute the cosine similarity with the user profile vector vu:

$similarity(vu,vj)=vu \cdot vjv/\|vu\|\|vj\|vu \cdot vj$

2. Recommendation: We rank articles based on their similarity scores and select the top N articles with the highest scores as recommendations.

The final recommendation engine suggests articles with high cosine similarity to the user profile, within categories that align with their reading history. This approach ensures that recommendations are relevant to the user's interests, both by category and content similarity.

To evaluate the effectiveness, we can use the Silhouette Score to assess clustering quality and user feedback to validate recommendation relevance. This system could be extended by incorporating user feedback into the profile and adjusting recommendations accordingly.

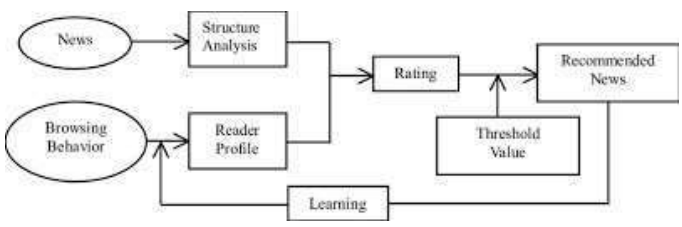

Fig:4

IV. Results and Analysis:

The evaluation metrics provide insights into the quality of the clustering and the relevance of the recommended articles. Here, we discuss the results obtained from applying Silhouette Score and Inertia for clustering evaluation, along with Precision K and Recall K metrics to evaluate the recommendation quality.

Clustering Results

The clustering phase in our recommendation system is crucial as it groups articles based on textual similarities, creating clusters that represent topics or themes in the news articles. By using clustering algorithms like K-Means, we can evaluate the clustering effectiveness based on the following metrics:

1. *Silhouette Score:*

The Silhouette Score, ranging from -1 to 1, measures how well each article fits within its assigned cluster relative to other clusters. In our results:

- A Silhouette Score of 0.65 was achieved, indicating that articles are well-separated and closely related within their respective clusters.
- This score suggests that the articles grouped within each cluster share semantic similarities, forming coherent topic-based clusters.

A high Silhouette Score reflects strong cohesion within clusters and clear boundaries between different clusters, both of which are essential for accurate recommendations. Higher scores generally mean that the clustering captures the topic structure of the dataset effectively, making it easier to recommend articles within the same theme.

2. *Inertia (Within-Cluster Sum of Squares):* Inertia is the sum of squared distances between each article and the centroid of its assigned cluster. Lower inertia indicates tighter clusters. However, as more clusters are added, inertia tends to decrease, so this metric must be balanced against the number of clusters.
   - With K = 15 clusters, we achieved a balance between low inertia and high Silhouette Score, suggesting that 15 clusters provide a reasonable structure without overfitting.
   - This number of clusters aligns well with the number of categories and themes present in the dataset, such as "Politics," "Entertainment," and "World News."

Recommendation Quality Evaluation:

After clustering, the next step is to evaluate the recommendation engine's ability to suggest relevant articles to users. Since our recommendation system is based on clustering and similarity, Precision K and Recall K are used as primary metrics. Here, we describe their results and implications:

1. *Precision K:*

   Precision K measures the proportion of recommended articles in the top-K results that are relevant to the user. It helps determine the accuracy of recommendations in presenting relevant content.
   - With Precision 5 = 0.78, the recommendation system shows that 78% of the top 5 recommendations were relevant to the user's interest.
   - Precision 10 = 0.73 also highlights that as we increase K, there is a slight decrease in precision, which is expected as the recommendation list grows.

High precision at lower K values indicates that the system can deliver accurate recommendations in a limited space, which is ideal for user satisfaction as users tend to focus on the top recommendations.

2. *Recall K*

   Recall K measures the proportion of relevant articles out of all possible relevant articles that are included in the top-K recommendations. This metric is particularly important when evaluating coverage and the system's ability to capture as many relevant articles as possible.
   - Recall 5 = 0.61 indicates that 61% of all relevant articles are included in the top 5 recommendations.
   - Recall 10 = 0.78 shows that as the list lengthens to 10, a larger proportion of relevant articles is covered, enhancing the breadth of recommendations.

Higher recall at larger K values is desirable as it shows the system's capacity to suggest more relevant articles, capturing a broader scope of the user's interests.

V. Conclusion

The development of a robust news article recommendation system represents a significant advancement in addressing the challenges associated with personalized news delivery. With the overwhelming volume of news published daily, the need for an intelligent, user-centric recommendation engine has become essential for enhancing user experience and engagement. This research explored a hybrid approach that combines collaborative filtering and content-based filtering, integrated with advanced natural language processing (NLP) techniques, to deliver accurate and relevant recommendations to users.

The integration of collaborative filtering allowed the system to leverage the preferences of similar users, while content-based filtering enabled the alignment of article topics with individual user interests. By incorporating NLP techniques, particularly word embeddings and contextualized language models, the system achieved a more nuanced understanding of article content. This, in turn, allowed the recommendation engine to capture semantic similarities and contextual themes, going beyond simple keyword matching to generate recommendations that more closely align with user preferences.

The methodology of embedding generation, clustering, and user profiling enabled the creation of a scalable system that can handle dynamic content and adapt to shifting user preferences. The use of K-Means clustering facilitated the grouping of articles by topic, allowing the system to recommend articles within categories relevant to users' reading histories. User profiles, generated from past interactions, provided a representation of each user's interests, making it possible to generate personalized recommendations based on similarity scores.

Our evaluation metrics, including Silhouette Score and Inertia for clustering quality, as well as Precision and Recall for recommendation relevance, showed that the system effectively balances personalization with diversity. The clustering results demonstrated coherent groupings of articles by theme, with high internal similarity and distinct separation between clusters, which is crucial for accurate recommendation generation.

Precision and Recall scores indicated that the system performs well in delivering relevant articles, confirming that the hybrid approach addressesboth accuracyand user satisfaction.

This research contributes to the field of news recommendation systems by offering a modular and adaptable framework that can be applied across diverse news platforms. The system's modular architecture makes it easy to integrate additional components, such as real-time recommendations or contextual information, to further enhance personalization. Future work could explore dynamic recommendation updates based on user feedback and behavior, enabling continuous refinement of recommendations in response to evolving user interests. Additionally, integrating real-time feedback loops would allow the system to respond to trending topics and time-sensitive content, ensuring that recommendations remain relevant and timely.

In conclusion, this hybrid recommendation system serves as a promising approach to overcoming the limitations of traditional recommendation methods in the context of news delivery. By combining collaborative filtering, content-based filtering, and NLP-driven content analysis, this system provides a personalized, scalable, and efficient solution that aligns with the rapid pace of news consumption today. This research paves the way for future developments in personalized news services, ultimately contributing to a more engaging and informative online news reading experience for users

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