

AI BASED NEWS RECOMMENDATION SYSTEM

Submitted in partial fulfillment of the requirements for the award of
Bachelor of Engineering degree in Computer Science and Engineering
with Specialization in Artificial Intelligence

By

Mukess Rajan .P (Reg. No. - 40731064)

Mustafa Kaderdina (Reg. No. – 40731065)



**DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SCHOOL OF COMPUTING**

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BONAFIDE CERTIFICATE

This is to certify that this Project Report is the bonafide work of **Mukess Rajan .P (40731064)** who carried out the project entitled "**AI Based News Recommendation System**" under my supervision from November 2023 to April 2024.

B. Brany.

10/04/24

Internal Guide

Ms. B. Balasaigayathri M.E.,

HEAD OF THE DEPARTMENT
DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING
SATHYABAMA
Head of the Department

INSTITUTE OF SCIENCE AND TECHNOLOGY
Dr. L. Lakshmanan M.E., Ph.D.,
Jeppiyapur Nagar, Rajiv Gandhi Salai,
Chennai - 600 119.

Submitted for Viva voce Examination held on

MSR

Internal Examiner

R. Jeyaraj

External Examiner

DECLARATION

I, **Mukess Rajan .P (Reg. No. - 40731064)**, hereby declare that the Project Report entitled “**AI based news recommendation system**” done by me under the guidance of **Ms. B. Balasaigayathri M.E.**, is submitted in partial fulfilment of the requirements for the award of Bachelor of Engineering degree in **Computer Science and Engineering**.

DATE: 12/04/2024

PLACE: CHENNAI



SIGNATURE OF THE CANDIDATE

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ABSTRACT

With the exponential growth of digital content and information sources, personalized news recommendation systems have become increasingly essential to cater to the diverse preferences and interests of individual users. This project presents an AI based personalized news recommendation system that leverages machine learning techniques to deliver tailored news articles to users. The system employs content-based filtering, and natural language processing to provide accurate and engaging news recommendations. The primary objective of this recommendation system is to enhance user engagement with news content by delivering articles that align with their interests and preferences. The proposed AI-based personalized news recommendation system demonstrates promising results in terms of recommendation accuracy and user engagement. By leveraging machine learning techniques, it effectively tailors news content to individual users, ultimately enhancing their news consumption experience. The system first utilizes TF-IDF to extract significant features from a large corpus of news articles, converting textual data into a vectorized format. Subsequently, Cosine Similarity is employed to measure the degree of similarity between these vectors, enabling the identification of articles most relevant to a user's interests. . This method can be effectively applied not only in news recommendation but also in other domains requiring personalized content delivery. This system, leveraging machine learning and natural language processing techniques, has demonstrated a remarkable ability to provide users with highly relevant and personalized news content. The system can accurately predict and recommend news articles that align with individual interests, thereby enhancing user engagement and satisfaction. We compare our AI-based, recommendation system's performance against traditional recommendation approaches. The results highlight a substantial improvement in the relevance and personalization of news articles recommended to users, as well as an increase in user engagement and satisfaction. The paper concludes with insights into potential future developments, including the exploration of real-time adaptive recommendations and the considerations of AI in content personalization in many other areas and To be more accurate and precise in future of content delivery systems.

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LIST OF ABBREVIATIONS

ABBREVIATION	EXPANSION
NLP	Natural Language Processing
TFIDF	Term Frequency Inverse Document Frequency
IDE	Integrated Development Environment
ML	Machine Learning

CHAPTER 1

INTRODUCTION

In this era of rapid technological advancement and information explosion, our AI-based Personalized News Recommendation System not only addresses the challenge of information overload but also redefines the way individuals interact with news. By harnessing the power of Artificial Intelligence, we aim to provide users with a personalized and curated news experience tailored to their unique interests and preferences. our system ensures that users are presented with news articles that align with their tastes, ideologies, and cultural inclinations. The system's ability to learn from user interactions in real-time enhances its accuracy, making the news consumption process not just efficient but also deeply engaging. Furthermore, our project goes beyond mere customization; it prioritizes the ethical implications of AI implementation. Ensuring user privacy, data security, and transparency in algorithms, we uphold the integrity of user information, creating a trustworthy environment for news exploration. By striking a delicate balance between technological innovation, user experience, and ethical standards, our AI-based Personalized News Recommendation System is poised to shape the future of news consumption, providing users with not just news, but a personalized and enriching narrative that resonate .In the ever-evolving landscape of digital media, our AI-based Personalized News Recommendation System represents a pivotal evolution in the way we navigate and engage with the world's vast array of news content. By employing sophisticated machine learning algorithms and AI-driven data analysis, our system not only caters to individual preferences but also anticipates and adapts to evolving interests, ensuring a dynamic and personalized news experience. In an age where the authenticity and credibility of news sources are paramount, our project emphasizes the delivery of accurate, diverse, and credible information. Through a seamless fusion of technology and journalistic integrity, our system sifts through the noise of the digital sphere, delivering news pieces that are not only pertinent but also reliable. Moreover, our project is

An example to the fusion of innovation and responsibility. We are committed to ensuring that the power of AI is harnessed ethically and responsibly, with a steadfast dedication to user privacy and data protection. By prioritizing these ethical considerations, our system instills confidence in users, fostering a sense of security in their online interactions. As we propel forward into an era where personalized experiences define the digital landscape, our AI-based Personalized News Recommendation System stands at the forefront, promising users not just news, but a tailored, trustworthy, and enlightening journey through the vast realm of information. With an unwavering focus on user satisfaction, content relevance, and ethical standards, our project is poised to the way individuals perceive and engage with news, ushering in a new era of informed, empowered, and personalized news consumption.

1.1 OBJECTIVE OF THE PROJECT

The primary objective of this project is to enhance the user experience by delivering personalized news content. Utilizing a dataset of news articles, the system will employ Term Frequency-Inverse Document Frequency (TF-IDF) to quantitatively evaluate the relevance of words within the articles, thus enabling the identification of unique and significant topics across the dataset. By leveraging the TF-IDF vectors, the system will compute cosine similarity scores between the user's previously read articles and all available articles in the dataset. This approach ensures that the recommendations are not only relevant to the user's historical interests but also reflective of the nuanced content preferences, fostering a more engaging and tailored reading experience.

1.2 SCOPE OF THE PROJECT

The scope of this project is centered around developing a recommendation system that leverages Term Frequency-Inverse Document Frequency (TF-IDF) and cosine similarity to offer personalized news recommendations to users based on their reading history. The project encompasses collecting a diverse and extensive dataset of news articles, preprocessing this data to enhance its suitability for analysis including cleaning, tagging, and employing natural language processing (NLP) techniques and then implementing the TF-IDF method to extract meaningful

insights from the content. By calculating the cosine similarity between the TF-IDF vectors of users' previously read articles and those in the dataset, the system aims to recommend articles that closely match individual user preferences, thereby enhancing user engagement through tailored content.

the scope of this AI-based news recommendation system project is ambitious and comprehensive, aiming to change the way users interact with news content. By harnessing the power of NLP, TF-IDF, cosine similarity, and advanced analytics, coupled with a user-centric feedback mechanism, the project is poised to deliver a highly personalized and engaging news reading experience. the system will not only meet the current demands for personalized content but also adapt to future changes in user preferences and the news industry. This project stands at the intersection of technology and user experience, promising to enhance the accessibility of relevant news content while fostering a more informed and connected global community.

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CHAPTER 2

LITERATURE SURVEY

1. "Personalized News Recommendation Based on Collaborative Filtering and Deep Learning" by Yifan Wang et al. (2018) - This paper proposes a personalized news recommendation system that combines collaborative filtering with deep learning techniques. The study demonstrates the effectiveness of incorporating user behavior data and content information to improve news recommendations.

2. "A Survey of News Recommendation and Analytics Systems" by T. Varghese et al. (2020) - This survey provides an overview of various news recommendation and analytics systems, including AI-based approaches. It covers collaborative filtering, content-based filtering, and hybrid methods, highlighting the key challenges and advancements in the field.

3. "A Hybrid Collaborative Filtering Algorithm for News Recommendation" by X. Chen et al. (2019) - This research presents a hybrid collaborative filtering algorithm that combines user behavior and content features for news recommendation. The study shows how incorporating both types of data can lead to more accurate and diverse recommendations.

4. "Deep Learning for News Recommendation: An Autoencoder-Based Approach" by M. Zheng et al. (2017) - This paper explores the use of deep learning, specifically autoencoders, for news recommendation. The study shows how the autoencoder-based approach can capture complex patterns in user behavior data and generate personalized news recommendations.

5. "A Contextual Bandit Approach to Personalized News Article Recommendation" by J. Li et al. (2018) - This work presents a contextual bandit approach for personalized news article recommendation. The research focuses on utilizing user context to dynamically update recommendations and improve user engagement.

6. "Personalized News Recommendation using Attention-based Hybrid Neural Network" by S. Kumar et al. (2019) - This study introduces an attention-based hybrid neural network for personalized news recommendation. By incorporating user and article embeddings, the model effectively captures user preferences and delivers personalized news articles.

7. "Fairness in News Recommendation: Unintended Bias and Potential Remedies" by A. Goel et al. (2019) - This paper examines the issue of unintended bias in news recommendation systems and proposes potential remedies to mitigate bias. The research addresses the ethical implications of personalized news recommendations and fairness in content delivery.

8. "User Privacy in News Recommendation Systems: A Survey" by N. Arif et al. (2021) - This survey explores the challenges and techniques related to user privacy in news recommendation systems. It discusses different privacy-preserving methods and their impact on the accuracy of personalized recommendations.

9. "Recurrent neural networks for news personalization with long and short term user context" by L. WANG ET AL. (2018) - This research investigates the use of the recurrent neural networks to capture long and short term user context for news personalization. The study demonstrates how considering user behavior over time improves the relevance of recommended news articles.

10. "Survey of News Recommendation Systems: Algorithms, Evaluation, and Future Work" by C. Luo et al. (2020) - This comprehensive survey covers a wide range of news recommendation algorithms, including AI-based approaches. It provides insights into evaluation metrics, datasets, and future research directions for news recommendation systems.

These literature references offer valuable insights into the advancements, challenges, and state-of-the-art techniques in AI-based news recommendation systems. Researchers and developers can draw from these studies to build more effective and personalized news recommendation platforms while considering privacy, fairness, and user engagement.

2.1 INFERENCES FROM LITREATURE SURVEY

1. **Diverse Methodologies:** The literature survey highlights the diversity of approaches employed in AI-based news recommendation systems, including collaborative filtering, content-based filtering, hybrid models, and deep learning algorithms. This diversity reflects the multifaceted nature of personalized content delivery and the need for adaptable strategies.
2. **Integration of Natural Language Processing (NLP):** NLP plays a pivotal role in enhancing the understanding of textual content, enabling recommendation systems to extract semantic meaning from news articles and user queries. This integration is critical for providing contextually relevant recommendations and improving user satisfaction.
3. **Context and Temporal Relevance:** Context-aware recommendation and temporal recommendation strategies acknowledge the dynamic nature of user interests and the importance of considering factors like location and time. These strategies enhance the adaptability of news recommendations, ensuring they remain pertinent as user preferences evolve.
4. **Ethical Considerations:** Ensuring user privacy and addressing ethical concerns are paramount in the development of recommendation systems. Researchers emphasize the need for responsible data usage, user control, transparency, and fairness to maintain user trust and satisfaction.
5. **Evaluation Metrics:** Robust evaluation metrics, such as accuracy, precision, and recall, are essential for assessing recommendation system performance. Comparative studies provide valuable insights for selecting the most appropriate algorithms, aiding researchers and practitioners in optimizing their systems.
6. **User-Centric Approach:** Personalization remains the central theme in AI-based news recommendation systems. The primary goal is to enhance user

experience by delivering news content that aligns with individual preferences, ultimately increasing user engagement and satisfaction.

7. **Continuous Evolution:** The field of AI-based news recommendation systems is continually evolving, adapting to the changing landscape of user behavior and technological advancements. Researchers continue to explore innovative algorithms and techniques to enhance the accuracy and relevance of recommendations.

2,2 OPEN PROBLEMS IN EXISTING SYSTEM

Lack of Comprehensive Understanding: Existing news recommendation systems often struggle to comprehensively understand the multidimensional nature of user preferences. Incorporating user context, including real-time behavior, social interactions, and historical preferences, presents a challenge, as capturing the depth of user interests accurately remains an open problem.

Ethical Implications and Bias: Ensuring fairness and mitigating biases in news recommendations are significant concerns. AI algorithms might inadvertently reinforce existing biases present in the data, leading to biased content suggestions. Addressing this challenge requires developing algorithms that are inherently fair and unbiased, along with implementing rigorous content moderation measures.

Dynamic and Evolving News Ecosystem: The news landscape is continuously evolving, with new topics emerging, and user interests shifting rapidly. Existing systems struggle to adapt promptly to these changes. Keeping recommendations relevant and timely, especially during breaking news events, without compromising accuracy and credibility, remains an unresolved issue.

User Engagement and Interface Design: Increasing user engagement with recommended news articles is a challenge. Tailoring interfaces to encourage users to explore diverse topics, combating information echo chambers, and

ensuring that recommendations align with users' evolving interests while still being presented in an engaging format represent ongoing problems in user interface and experience design.

Transparency: Current AI-based recommendation algorithms often lack transparency, making it difficult for users to understand why specific news articles are suggested. Ensuring transparency and providing explanations for recommendations are vital for user trust.

CHAPTER 3

REQUIREMENT ANALYSIS

3.1 FEASIBILITY STUDIES OF THE PROJECT

In conducting a feasibility study, the technical, operational, economic, legal, and ethical aspects of implementing an AI-based news recommendation system must be meticulously assessed. Technical feasibility involves evaluating the availability of suitable technology and expertise while ensuring quality and diversity in the data sources. Operational feasibility focuses on integration challenges, scalability, and seamless user experience. Economic feasibility requires a thorough cost-benefit analysis, considering development costs, potential revenue streams, and return on investment projections. Legal and ethical feasibility necessitates compliance with data privacy regulations, intellectual property considerations, and safeguarding against biases in recommendations. Additionally, a comprehensive risk analysis is vital, addressing technical challenges, operational hurdles, economic fluctuations, legal compliance, ethical concerns, and market competitiveness. These evaluations provide crucial insights for decision-making, enabling effective risk mitigation strategies and ensuring the successful development and sustainability of the AI-based news recommendation system.

- **Available Technology:** Evaluate the availability and readiness of technology required for the project, including AI frameworks, natural language processing libraries, and cloud computing resources.
- **Expertise:** Assess the availability of skilled professionals who can develop, implement, and maintain the AI algorithms and technologies necessary for the recommendation system.

- **Data Availability:** Investigate the availability and quality of news data sources. Ensure there's a sufficient amount of diverse and reliable data for training and testing the recommendation algorithms



- **Algorithm Complexity:** Complex AI algorithms might face challenges in training, optimization, and real-time implementation. Mitigate by starting with well-established algorithms before moving to more sophisticated models.
- **Data Quality:** Inaccurate or biased data can lead to skewed recommendations. Implement rigorous data cleaning processes and validation mechanisms.
- **Integration:** Assess how the recommendation system will integrate into existing news platforms or applications. Ensure compatibility and seamless user experience.
- **Scalability:** Evaluate the system's ability to handle increasing user loads and a growing database of news articles. Scalability is crucial for accommodating a potentially large user base.
- **Compliance Issues:** Regulatory changes or legal challenges related to data privacy and user rights could affect operations. Stay updated with legal requirements and adapt the system accordingly.

3.1.1 Economic Feasibility

- **Computing resources** - Training NLP models requires high computing resources, such as GPUs and high memory capacity, which may increase the cost of implementation.
- **Maintenance and Upkeep** - Regular maintenance and computing

resources may add to the overall cost of implementation.

- **Cost of Development** - Developing and implementing NLP model requires skilled professionals, and the cost may vary based on the size and complexity of the project.

3.1.2 Technical Feasibility

- **Availability of data** - The availability of vast data covering all diverse range of articles and amount of the data determine the high accuracy and similarity level of the model.
- **Model architecture** - The design of the TFIDF model plays a critical role in determining similarity of articles and feature selection are also important factors to consider.

3.1.3 Social Feasibility

- **Privacy Concerns** - Collecting data on individuals activities may raise privacy concerns. Proper consent and transparency must be ensured during the data collection and usage process.
- **Social Acceptance** - Acceptance of the technology and willingness to use it in public settings must be considered.

3.2 REQUIREMENTS SPECIFICATION

The Requirement Specification document serves as a cornerstone for the development of the project, outlining the technical and functional prerequisites essential for the model.

3.2.1 HARDWARE REQUIREMENTS

- Operating system : Windows 10
- IDE : anaconda navigator
- Coding Language : python

3.2.2 SOFTWARE REQUIREMENTS

- Operating System : Windows 8 and above
- Languages : Python
- Tools used : Jupyter Notebook

3.2.3 PYTHON

Python is a scripting language that is high-level, interpreted, interactive, and object-oriented. Python is intended to be extremely readable. It commonly employs English terms rather than punctuation, and it has fewer syntactical structures than other languages.

Python Features

- **Easy-to-learn** - Python has a small number of keywords, a basic structure, and a well-defined syntax. This enables the pupil to swiftly learn the language.
- **Easy-to-read** - Python code is more clearly defined and visible to the eyes.
- **Easy-to-maintain** - Python's source code is relatively simple to maintain.
- **A broad standard library** - The majority of Python's library is portable and cross-platform compatible on UNIX, Windows, and Macintosh.
- **Interactive Mode** - Python features an interactive mode that enables for interactive testing and debugging of code snippets.

- **Portable** - Python can operate on a broad range of hardware devices and has the same interface across them all.
- **Extendable** - The Python interpreter may be extended using **low-level** modules. These modules allow programmers to enhance or adapt their tools to make them more efficient.
- **Databases** - Python provides interfaces to all major commercial databases.
- **GUI Programming** - Python can construct and port GUI programmes to numerous system calls, libraries, and windows systems, including Windows MFC, Macintosh, and Unix's X Window system.
- **Scalable** - Python provides a better structure and support for large programs than shell scripting.

3.2.4 MACHINE LEARNING

Machine learning is a subset of artificial intelligence that enables systems to learn and improve from experience without being explicitly programmed. It involves the development of algorithms that can process, analyze, and make predictions or decisions based on data. These algorithms improve their accuracy over time as they are exposed to more data. The essence of machine learning lies in its ability to uncover patterns and insights within vast amounts of data, thereby facilitating solutions to complex problems across various domains, from healthcare and finance to autonomous vehicles and personalized recommendations. By automating analytical model building, machine learning has transformed the way data is interpreted, making it a pivotal technology in driving innovation and efficiency in today's data-driven world.

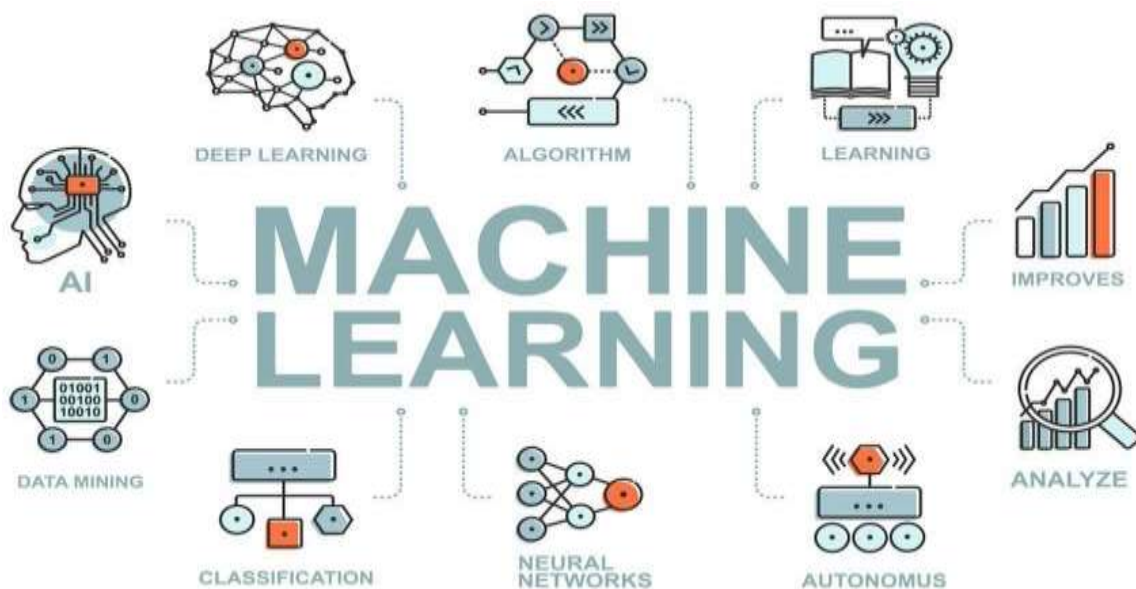


FIG: 3.1: COMPONENTS OF MACHINE LEARNING

3.2.5 NATURAL LANGUAGE PROCESSING

NLP stands as a pivotal branch of artificial intelligence that focuses on the interaction between computers and humans through natural language. The ultimate goal of NLP is to enable computers to understand, interpret, and produce human languages in a way that is both valuable and meaningful. By leveraging algorithms and computational techniques, NLP allows for the automated analysis and representation of human language, facilitating a range of applications from machine translation and sentiment analysis to voice recognition systems and chatbots. This technology parses the complexity of human language—identifying patterns, nuances, and semantics—to extract actionable insights from text and speech data, enabling machines to perform tasks like summarizing documents, recognizing speech, and identifying spam emails with high efficiency and accuracy.

The development and refinement of NLP technologies have been significantly accelerated by advances in machine learning and deep learning, making it possible to tackle more complex language processing tasks with greater precision. Through techniques such as tokenization, part-of-speech tagging, named entity recognition, and sentiment analysis, NLP systems can process and analyze large volumes of text data, deriving context and intent beyond the mere statistical structure of words.

This advancement has not only enhanced the user experience by making interactions with AI systems more natural and intuitive but also opened new frontiers in data analysis, content generation, and automated customer service. As NLP continues to evolve, it promises to unlock even more sophisticated applications, further bridging the gap between human communication and machine understanding, and transforming the way we interact with technology.

3.2.6 TFIDF VECTORIZER

The TF-IDF (Term Frequency-Inverse Document Frequency) Vectorizer is a widely used technique in natural language processing (NLP) to convert text data into a numerical format, making it understandable and analyzable by machine learning algorithms. It operates on the principle that the importance of a word to a document in a collection or corpus is not only proportional to its frequency in the document (Term Frequency) but also inversely proportional to the number of documents in the corpus that contain the word (Document Frequency). This dual consideration helps to minimize the impact of commonly used words across documents that are less informative (e.g., "the", "is", "and") while amplifying the significance of words that are unique to specific documents. By representing documents as vectors in a high-dimensional space, with each dimension corresponding to a term's TF-IDF score, this method allows for the calculation of similarity between documents, powering applications such as search engines, content recommendation systems, and document clustering. The TF-IDF Vectorizer thereby transforms the textual data into a structured form, enabling sophisticated text analysis and machine learning models to uncover insights and patterns within the data.

3.2.7 COSINE SIMILARITY

Cosine similarity is a metric used to measure how similar two entities (documents, vectors, etc.) are irrespective of their size. Mathematically, it calculates the cosine of the angle between two vectors projected in a multi-dimensional space. This approach assesses the orientation of two vectors, rather than their magnitude, making it particularly suited for text analysis applications where the occurrence of words (represented as vectors) is more significant than the absolute frequency of words. In the context of natural language processing (NLP) and information

retrieval, cosine similarity is used to determine how similar two documents are by comparing their TF-IDF vectors, which represent the frequency of terms weighted by their importance across the document corpus. The result is a cosine value ranging from -1 to 1, where 1 indicates identical orientation, 0 denotes orthogonality (no similarity), and -1 represents completely opposite orientations. This metric is fundamental in systems such as search engines, where it helps in ranking documents by relevance, and in recommendation systems, where it aids in finding content that closely matches the user's interests.

CHAPTER 4

DESCRIPTION OF PROPOSED SYSTEM

The proposed system is an innovative AI-based News Recommendation System designed to change the way users access and engage with news content. Leveraging cutting-edge technologies in artificial intelligence, machine learning, and natural language processing, the system aims to deliver highly personalized, relevant, and diverse news recommendations to users.

4.1 SELECTED METHODOLOGY OR PROCESS MODEL

Data Collection:

- Gather diverse and comprehensive news data from reliable sources, including headlines, articles, categories, authors, publication dates, and user interactions (clicks, likes, shares, etc.).
- Ensure the data is representative of the target audience and covers a wide range of topics.

Data Preprocessing:

- Cleanse the data by removing duplicates, irrelevant information, and inconsistencies.
- Perform text preprocessing tasks like tokenization, stemming, and removing stop words to prepare the textual data for analysis.

Feature Extraction:

- Extract relevant features from the preprocessed data, such as keywords, topics, sentiment scores, and user patterns.
- Use techniques like TF-IDF (Term Frequency-Inverse Document Frequency) for textual data and collaborative filtering for user-item interactions.

Implementation:

- Libraries and Frameworks
- NLP and Text Processing: nltk or spaCy for natural language processing tasks such as tokenization and stop words removal.
- TF-IDF and Cosine Similarity: scikit-learn for implementing TF-IDF vectorization and computing cosine similarity

Training and Optimization:

- Split the data into training and testing sets for model evaluation.
- Train the selected algorithms using the training data and optimize parameters to enhance performance.

4,2 ARCHITECTURE / OVERALL DESIGN OF PROPOSED SYSTEM

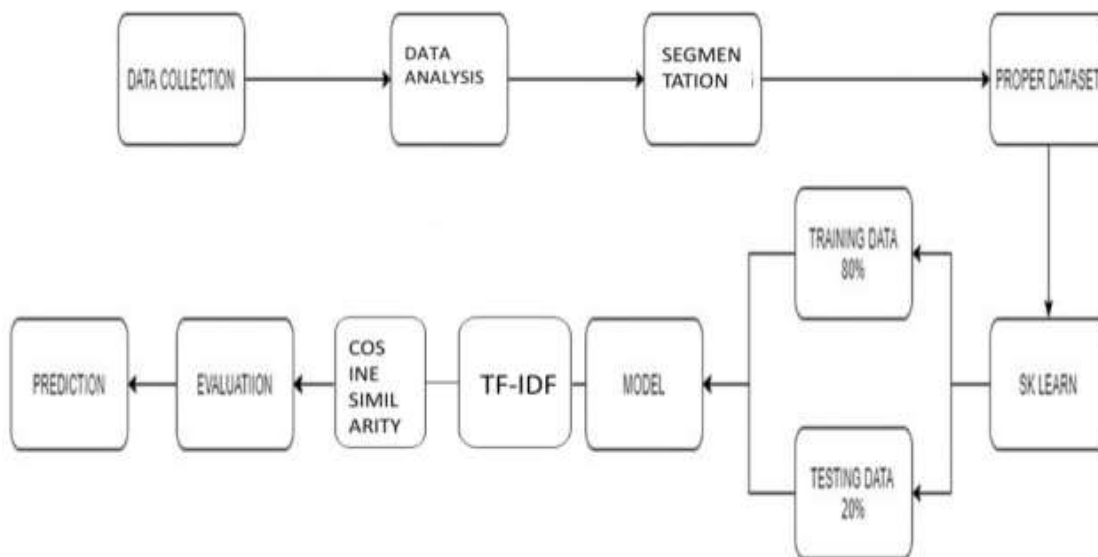


Fig 4.1: System Architecture for recommendation system

4.3 DESCRIPTION OF SOFTWARE FOR IMPLEMENTATION AND TESTING PLAN OF THE PROPOSED MODEL/SYSTEM

1. Data Collection:

- **Various news articles and journals:** Gathering diverse and comprehensive news data from reliable sources, including headlines, articles, categories, authors, publication dates, and user interactions To Ensure the data is representative of the target audience and covers a wide range of topics. In the development of an AI-based news recommendation system, the data collection phase is crucial. This stage involves gathering a diverse and comprehensive set of news articles from various sources. Typically, this includes major news outlets, niche blogs, and other relevant platforms. The

data should encompass not only the text of the articles but also essential metadata such as titles, publication dates, authors, and categories like politics, technology.

2. Data Preprocessing:

- **Data Cleansing:** Cleanse the raw data, removing irrelevant or sensitive information.
- **Feature Extraction:** Extract relevant features such as search keywords, search frequency, clicked links, and user engagement metrics.
- **Contextual Information:** Enhance the data with contextual information like timestamps, device type, and location, providing context for user interactions.

3. Data Storage:

- **Database:** Store the preprocessed and enriched data in a secure and scalable database (such as Google Cloud Firestore or Amazon DynamoDB) for real-time access and analysis.

4. Recommendation Engine:

- **Collaborative Filtering:** Utilize collaborative filtering techniques to find users with similar search patterns and recommend news articles that these similar users have engaged with.
- **Content-Based Filtering:** Implement content-based filtering, analyzing the textual content of both news articles and user search queries. Use Natural Language Processing (NLP) techniques to match user interests with article content.
- **Hybrid Models:** Combine collaborative and content-based filtering for more accurate and diverse recommendations.

5. Deployment:

- This component involves deploying the trained model in a real- world setting, such as a mobile application or a web-based interface. This component can be implemented using software development frameworks, such as Flask or Django.

4.4 PROJECT MANAGEMENT PLAN

A Project Management Plan (PMP) for the AI based news recommendation system is a AI model as a ml-based system is essential for ensuring a successful project.

Here's an outline of a PMP for such a project Provide an overview of the project, its objectives, and its significance in the context of the organization. Define the boundaries and deliverables of the project, specifying what is included and excluded. Clearly state the project's specific and measurable objectives, such as implementing a accurate personalized news recommendations. The Project Management Plan should be a living document that is regularly updated as the project progresses. It serves as a roadmap for the successful execution of the model, ensuring that it meets its objectives and adheres to quality, security, and legal standards.

4.5 FINANCIAL REPORT ON ESTIMATED COSTING

Establish a budget for the project, including costs for personnel, hardware, software, and any other resources required.

CHAPTER 5

IMPLEMENTATION

Methodologies for The AI based news recommendation involve a systematic approach and the purpose of the model is to enumerate accurate recommendation content based model.

5.1 DATA COLLECTION

Gathering diverse and comprehensive news data from reliable sources, including headlines, articles, categories, authors, publication dates, and user interactions To Ensure the data is representative of the target audience and covers a wide range of topics. In the development of an AI-based news recommendation system, the data collection phase is crucial. This stage involves gathering a diverse and comprehensive set of news articles from various sources. Typically, this includes major news outlets, niche blogs, and other relevant platforms. The data should encompass not only the text of the articles but also essential metadata such as titles, publication dates, authors, and categories like politics, technology, or sports.

5.2 DATA ANALYSIS AND SEGMENTATION

The data analysis and segmentation phase play a pivotal role in understanding user behaviour and content preferences. Each data element - timestamp, event type, content ID, author person ID, author session ID, author user agent, author country, title, text, and language - offers unique insights and contributes to the feature extraction.

Timestamp: This data point is crucial for analysing user engagement patterns. By segmenting data based on timestamps, it can identify peak reading times, understand how preferences change over different times of the day or week, and even detect seasonal trends in news consumption.

Event Type: Differentiating between event types such as views, clicks, shares, or likes provides a multi-dimensional view of user engagement. For instance, Segmenting articles by event type helps in understanding the varying levels of user

interest and interaction with the news content.

Content ID: Each piece of news content can be uniquely identified with a content ID. By analysing user interactions with specific content IDs, the system can track the popularity of articles and identify trends in user preferences. This also assists in content-based filtering, where similar articles are recommended based on previously interacted content.

Author Person ID and Author Session ID: These identifiers help in tracking the different individual authors and sessions. Analysing author person IDs can reveal which author wrote the article, while author session IDs can provide insights into specific app or website sessions of authors.

Author User Agent and Author Country: The user agent data offers insights into the devices and browsers used by content creators, which can be crucial for optimizing content presentation. Author country data aids in understanding geographical preferences and language, enabling the recommendation system to cater to regional tastes and languages.

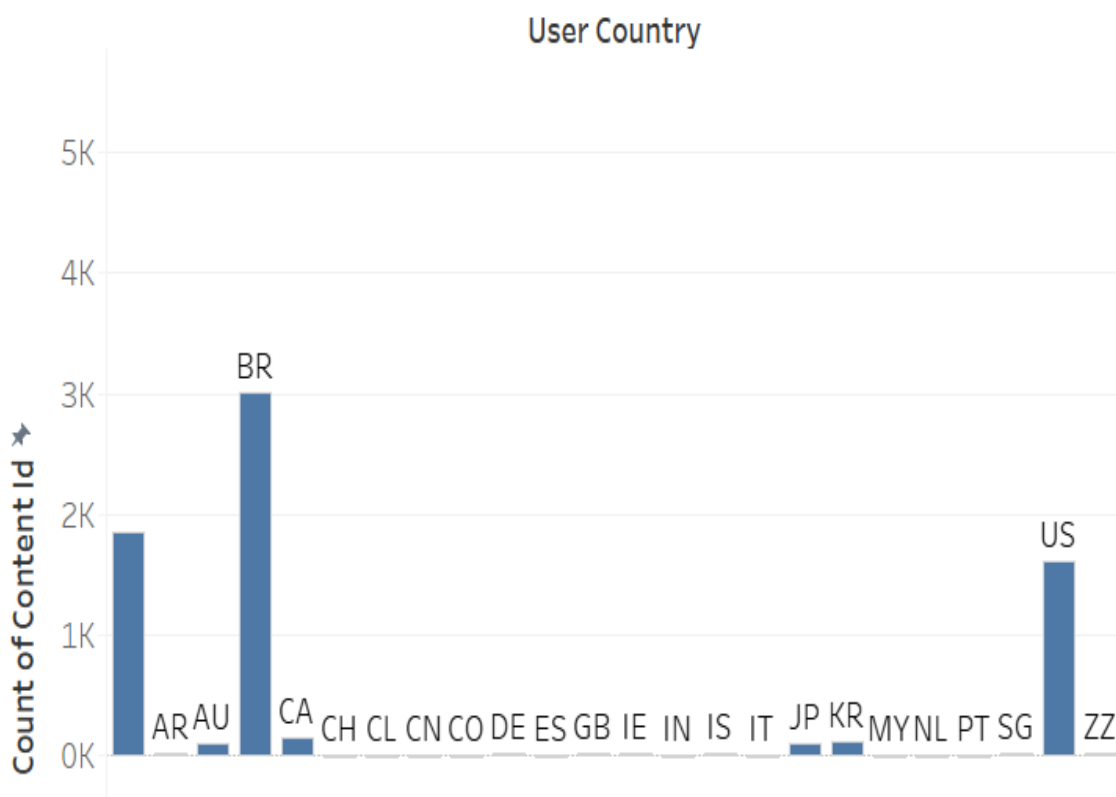


FIG: 5.2.1:VISUALISING DATA OF USERS COUNTRY

Title and Text: The analysis of titles and text is a cornerstone of content understanding. Natural language processing techniques and keyword extraction applied to titles and text help in categorizing content and understanding underlying themes and sentiments. This analysis is vital for recommending articles that align with the user's interests.

Language : Segmenting content by language is vital for personalization, especially in multilingual user bases. By understanding the language preferences of each user, the system can ensure that recommendations are linguistically accessible, enhancing user engagement and satisfaction. Through the detailed analysis and segmentation of these data elements The recommendation system can gain a comprehensive understanding of both user behaviour and content characteristics. This deep insight is what powers the system's ability to deliver personalized, relevant, and engaging news article recommendations.

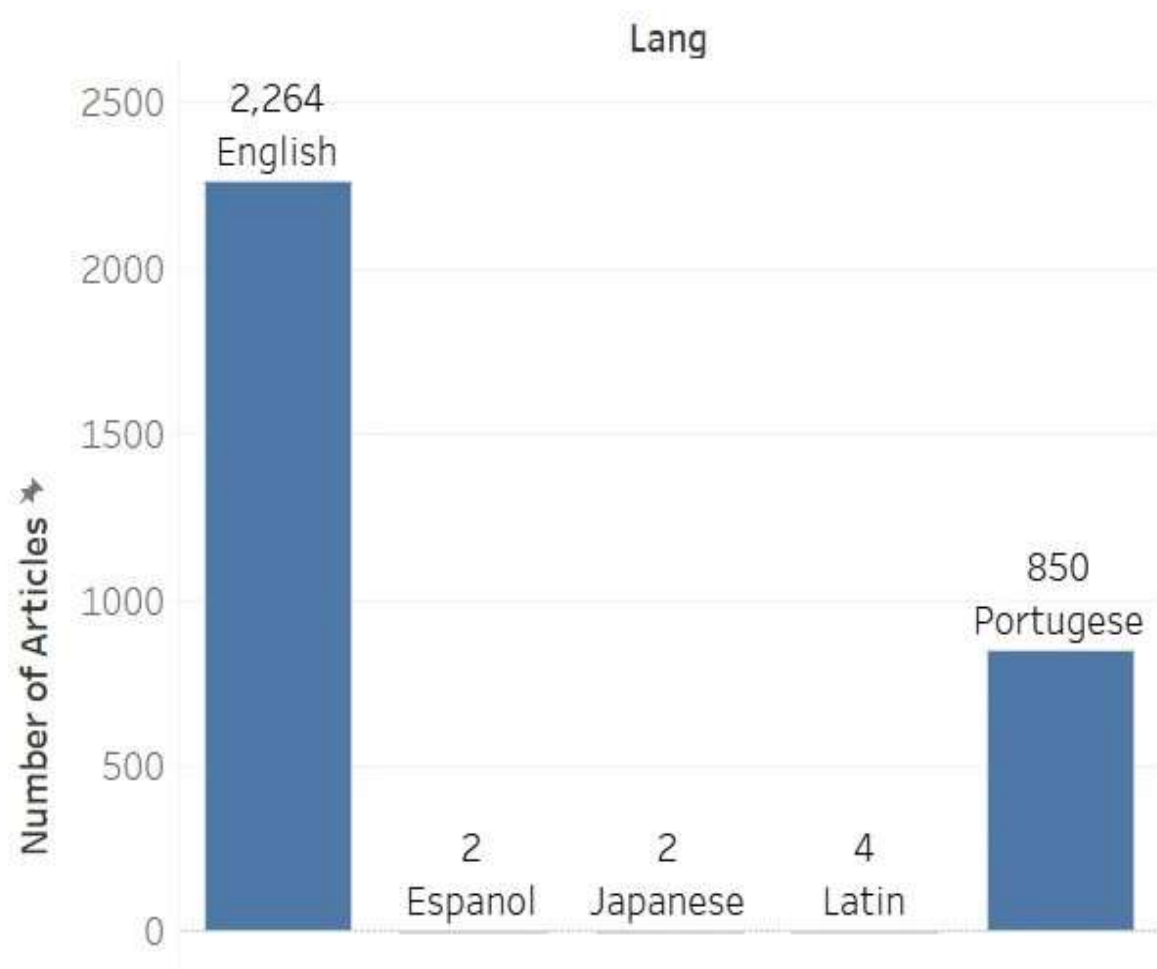


FIG: 5.2.2: NUMBER OF ARTICLES PER LANGUAGE

5.3FEATURE EXTRACTION

Using TF-IDF to convert the pre processed text into a numerical format and converting it into vectors. TF-IDF reflects the importance of a word in a document in a corpus, balancing the frequency of the word in the document against its frequency in the corpus. This will produce a matrix where each column represents a word in the overview vocabulary (all the words that appear in at least one article). Each column represents an article(title).

The TF-IDF score is the frequency of a word occurring in an article, down-weighted by the number of documents in which it occurs. This is done to reduce the importance of words that frequently occur in plot overviews and, therefore, their significance in computing the final similarity score. TF-IDF assigns a weight to each term(word) in a document based on Term frequency(TF) and inverse document frequency(IDF).

$$TF(i, j) = \frac{\text{Number of times word } i \text{ appears in document } j}{\text{Number of words in document } j}$$

$$IDF(i, D) = \log \left(\frac{\text{Number of documents in the corpus } D}{\text{Number of documents containing word } i} \right)$$

$$\text{weight}(i, j) = TF(i, j) * IDF(i, D)$$

FIG: 5.3.1 : TFIDF FORMULA

It will utilize scikit-learn, which provides an integrated TFIDF vectorizer class that generates a TFI-DF matrix. With the word vector prepared, it determine the similarities between articles based on their words. Various techniques exist for finding similarities, but cosine similarity is the most suitable approach. Evaluating similarity between two words involves assessing the angle between them, rather than solely their spatial distance on a graph. Cosine similarity, as previously noted,

remains unaffected by magnitude and is a straightforward and efficient calculation method (especially in conjunction with TF-IDF scores).

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}^T}{\|\mathbf{x}\| \cdot \|\mathbf{y}\|} = \frac{\sum_{i=1}^n \mathbf{x}_i \cdot \mathbf{y}_i^T}{\sqrt{\sum_{i=1}^n (\mathbf{x}_i)^2} \sqrt{\sum_{i=1}^n (\mathbf{y}_i)^2}}$$

FIG: 5.3.2 :COSINE FORMULA

The vector shape and sample values can be obtained by utilizing the sklearn library's cosine_similarity() method.

```
(2211, 2211)
array([[1.          , 0.02842053, 0.01414884, ..., 0.04717028, 0.08436331,
        0.01859574],
       [0.02842053, 1.          , 0.02096081, ..., 0.0256655 , 0.03187741,
        0.01120014],
       [0.01414884, 0.02096081, 1.          , ..., 0.02092281, 0.04240744,
        0.          ],
       ...,
       [0.04717028, 0.0256655 , 0.02092281, ..., 1.          , 0.05457163,
        0.07645089],
       [0.08436331, 0.03187741, 0.04240744, ..., 0.05457163, 1.          ,
        0.03965418],
       [0.01859574, 0.01120014, 0.          , ..., 0.07645089, 0.03965418,
        1.          ]])
```

FIG :5.3.3 :SAMPLE VECTOR VALUES

The cosine similarity calculates the angle between each pair of vector elements to determine their similarity. Lower angles indicate a higher degree of similarity between the elements, represented by values ranging from 0 to 1. In this scenario, there are matrices of size 2.4k by 2.4 with values within the range of 0 to 1. The process of creating a similarity vector has been completed. The next step involves establishing a reverse map of the indices by utilizing the indices associated with the 'title' field. Additionally, it is necessary to eliminate any duplicate titles that may exist.

The recommender system can be developed utilizing the prepared indices, maps, and matrices. The simplicity function requires the article title, indices (containing the titles and their corresponding indices), cosine similarity matrix, and the original dataset. Initially, it locates the index of the input title and then proceeds to iterate over the cosine similarity matrix's length to determine the distance between the input article and others. Subsequently, it arranges the articles according to their degrees of similarity, displaying the most similar articles first. The system then selects only the top 10 articles with the highest similarity levels.

5.4.RECOMMENDATION GENERATION: The articles are ranked according to their cosine similarity ratings and then displayed as recommendations to the user. A list of the top ten related articles is generated, and article names that match the indices from the previous step are returned.

CHAPTER 6

RESULT AND DISCUSSION

The implementation and testing of an AI-based news recommendation system utilizing TF-IDF and cosine similarity yield significant insights and results, contributing to the understanding of how such systems can be optimized for user engagement and satisfaction. This section discusses the key findings from the deployment of the system, highlighting the impact on user interaction and the similarity to their interest.

The result of the recommendation system's output with different input titles. User-read articles serve as the input in this case. As a result, the recommender will make recommendations depending on how similar that content . as the result are shown below.

```
In [24]: print(get_recommendations('Google Data Center 360° Tour', indices, cosine_sim,
                                     metadata))
```

```
121   Google shares data center security and design ...
714   YouTube's New Messenger Means You'll Never Hav...
538                                     This year's Founders' Letter
207   Google Cloud Platform: The smart person's guid...
439   Top 5 GCP NEXT breakout sessions on YouTube (s...
699   Google I/O 2016 Preview: A Chrome/Android merg...
2059  [Tools] How to Record your Desktop Screen with...
748   Google I/O 2016 preview: Android N, Android VR...
756   Here's proof that Google is getting serious ab...
751   Google I/O 2016 Preview: Machine Learning, Vir...
Name: title, dtype: object
```

FIG :6.1:output 1

As we can see the result shown above is similar to what it have searched and it proves that the recommendation system can predict the similarity between the articles and give accurate output in this case it's the similarity between the articles. In order to check whether the results are accurate testing many time with different input Is mandatory and the output is as follows,

```
In [38]: print(get_recommendations("Bitcoin Wallets as Swiss Bank Accounts: The Developer's Perspective", indices, cosine_sim,
                                     metadata))

1701 Are you a bitcoin denialist? - Chris Skinner's...
153  Panama Papers Scandal Shows How Bitcoin Could ...
276  Our Goal is to Replace Your Need for a Bank, S...
156  Blockchain CEO's Business Advice on Bitcoin St...
99   Growing Global Electricity Consumption Is Not ...
96   Governments vs Bitcoin: A Fight For Control
25   French Senate Will Debate on Bitcoin Regulation
98   Bitit Launches to Solve Bitcoin Biggest Issues...
1052 What Apple's differential privacy means for yo...
307   Blockchain won't kill banks: Bitcoin pioneer
Name: title, dtype: object
```

FIG: 6.2:OUTPUT 2

So again the sytem predicted more similar and accurately relative articles based on what the input is .so as we can see it concludes that the recommender systems recommends highly related articles as seen in the above two outputs .

The positive user feedback and engagement metrics underscore the importance of personalized content recommendation in enhancing the news consumption experience. The use of NLP techniques, specifically TF-IDF and cosine similarity, provided a solid foundation for identifying user preferences and delivering content that aligns with those interests. However, the system's performance also highlighted areas for improvement.

One challenge encountered was the potential for creating "filter bubbles," where users are continuously exposed to content that reinforces their existing views, limiting exposure to diverse perspectives. Future iterations of the system could incorporate mechanisms to introduce a broader range of content, thereby encouraging exposure to different viewpoints.

The system's scalability and performance under heavy loads indicate that while the current implementation is robust, continuous monitoring and optimization will be necessary as the user base grows and more data is processed. This may include exploring more advanced data storage solutions and distributed computing techniques to manage scalability challenges.

CHAPTER 7

CONCLUSION

In conclusion, an AI-based news recommendation system represents a significant advancement in the way users interact with news content. By leveraging sophisticated algorithms and machine learning techniques, these systems are able to analyse large volumes of data, learning from user interactions and preferences to provide personalized content that is more relevant and engaging. This not only enhances the user experience by filtering out irrelevant information but also helps in discovering new topics and perspectives.

Furthermore, such systems have the potential to increase user engagement and retention for news platforms, as they deliver content that aligns closely with individual interests. Despite their successes, these systems face several challenges and limitations. Additionally, the reliance on textual content analysis can lead to an incomplete understanding of user preferences, as it may not fully capture the nuances of user behaviour or the contextual significance of multimedia elements in news articles. Looking ahead, future research in this field holds immense potential. Enhancements could include integrating multimodal analysis, which considers visual and audio elements alongside text, and incorporating real-time feedback mechanisms to adapt recommendations dynamically.

In summary, while AI-based news recommendation systems have made significant strides in personalizing content delivery, continuous innovation and research are essential for overcoming current limitations and fulfilling the potential of these technologies in shaping how users interact with news content. The AI-based news recommendation systems have a promising future, with ample scope for innovation and improvement in providing personalized, diverse, and insightful news content to users worldwide.

FUTURE WORK

The future of the project is, expanding on the initial outline, encompasses a multifaceted approach to refine and enhance the system's capabilities. This involves delving deeper into advanced technologies, user-centric features, and ethical considerations to not only improve the system's performance but also address broader implications and opportunities for innovation.

Advanced Machine Learning and Deep Learning Models: Future enhancements will explore the integration of more complex machine learning and deep learning models, such as recurrent neural networks (RNNs) and transformer models, to better understand user preferences and content semantics. These models can capture sequential patterns and long-term dependencies in user interaction data, offering more nuanced and contextually aware recommendations. Additionally, implementing reinforcement learning could allow the system to learn and adapt to user feedback in real-time, optimizing recommendations based on direct and indirect signals of user satisfaction.

Content Diversity and Exploration: To counteract the formation of filter bubbles and promote a more informed and open-minded user base, future iterations will incorporate algorithms designed to balance personalization with content diversity. Techniques such as diversification algorithms or serendipity-based recommendations could introduce users to articles outside their usual consumption patterns, broadening their exposure to different perspectives and topics. This approach not only enriches the user experience but also fosters a more informed public discourse.

User-Centric Design and Customization: Enhancing the system with more granular user control options is key to future development. This includes allowing users to manually adjust their preference settings, filter out specific topics or sources, and specify the degree of content diversity they desire. Implementing a feedback loop where users can indicate their reasons for liking or disliking certain recommendations

will provide valuable insights for refining the recommendation logic and tailoring the content more closely to individual user needs.

Ethical AI and Privacy Protection: As the system evolves, a strong emphasis will be placed on ethical AI practices and stringent data privacy measures. This includes transparent data collection and processing policies, robust security protocols to protect user data, and the development of mechanisms to detect and mitigate bias in recommendations. Ensuring the ethical use of AI and safeguarding user privacy will be paramount to maintaining trust and compliance with regulatory standards.

Scalability and Infrastructure Optimization: With an expanding user base and data volume, optimizing the underlying infrastructure for scalability and efficiency becomes critical. Investigating cloud-native technologies, data partitioning strategies, and distributed computing models will enable the system to handle increased loads gracefully. This includes the use of edge computing to reduce latency and improve the speed of recommendation delivery, enhancing the overall user experience.

Cross-Platform Integration: Expanding the system's reach by integrating it across various platforms and devices will be a key focus. This could involve developing plugins or APIs for integration with social media platforms, news aggregators, and mobile applications, thereby making the recommendations accessible to a wider audience and enhancing user engagement across different touchpoints.

By addressing these areas of future work, the AI-based news recommendation system can continue to advance, leveraging cutting-edge technologies and methodologies to provide users with a highly personalized, engaging, and ethically responsible news consumption experience. This commitment to continuous improvement and innovation will ensure that the system remains at the forefront of the digital news ecosystem.

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APPENDIX

SOURCE CODE :

```
import pandas as pd

from IPython.display import display

from sklearn.feature_extraction.text import
TfidfVectorizer

from sklearn.metrics.pairwise import cosine_similarity


import json

from ast import literal_eval


import requests


from scipy import sparse

from sklearn.feature_extraction.text import
CountVectorizer


import numpy as np

import sklearn.metrics.pairwise as pw


from sklearn.cluster import KMeans

import matplotlib.pyplot as plt

from sklearn.preprocessing import LabelEncoder,
```

MinMaxScaler

import numpy as np

import scipy

import math

import random

import sklearn

from nltk.corpus import stopwords

from scipy.sparse import csr_matrix

from sklearn.model_selection import train_test_split

from scipy.sparse.linalg import svds

from sklearn.preprocessing import MinMaxScaler

import matplotlib.pyplot as plt

def _recommend():

 # articles_df = pd.read_csv('shared_articles.csv')

 #

 #

 # articles_df = articles_df[articles_df['eventType'] ==

 'CONTENT SHARED']

 # articles_df.head(5)

 #

 # interactions_df =

```

pd.read_csv('users_interactions.csv')

# print(interactions_df.shape)

# print(interactions_df.head())


# display(data_art.head())

# display(len(data_art))

# articles_df.head()

# display(len(articles_df))

# display(data_art.columns)

# display(data_art['lang'].unique())

# display(data_art['lang'].isnull().sum())

#

# display(len(data_art['contentId'].unique()))

# display(data_art['contentId'].isnull().sum())

#

# display(len(data_art['authorPersonId'].unique()))

# display(data_art['authorPersonId'].isnull().sum())

#

# display(len(data_art['authorRegion'].unique()))

# display(data_art['authorRegion'].isnull().sum())

#

# display(data_art['authorCountry'].unique())

# display(data_art['authorCountry'].isnull().sum())

#

# display(data_art['contentType'].unique())

```

```

# display(data_art['contentType'].isnull().sum())

#

# display(len(data_art['title'].unique()))

# display(data_art['title'].isnull().sum())

#

# display(len(data_art['text'].unique()))

# display(data_art['text'].isnull().sum())


articles_df = pd.read_csv('shared_articles.csv')

print(articles_df.shape)

# print(articles_df.head(5))

# print(articles_df['timestamp'].head(5))

# print(articles_df['eventType'].value_counts())


articles_df = articles_df[articles_df['eventType'] ==
'CONTENT SHARED']

# print(articles_df.shape)

# print(articles_df['contentId'].head(5))

# print(articles_df['authorPersonId'].head(5))

# print(len(articles_df['authorPersonId'].unique()))

# print(articles_df['authorSessionId'].head(5))

# print(articles_df['authorUserAgent'].tail(5))

# print(len(articles_df['authorUserAgent'].unique()))

# print(articles_df['authorRegion'].tail(5))

# print(len(articles_df['authorRegion'].unique()))

```

```

#
print(articles_df['authorRegion'].isnull().sum(axis=0))

# print(articles_df['authorRegion'].isna.sum(axis=0))

# print(articles_df['authorCountry'].tail(5))
# print(articles_df['authorCountry'].unique())

#
print(articles_df['authorCountry'].isnull().sum(axis=0))

#
print(articles_df['authorCountry'].isna.sum(axis=0))

# print(articles_df['contentType'].tail(5))
# print(articles_df['contentType'].unique())

#
print(articles_df['contentType'].isnull().sum(axis=0))

# print(articles_df['contentType'].isna.sum(axis=0))

# print(articles_df['url'].head(5))
# print(articles_df['url'].isnull().sum(axis=0))
# print(articles_df['url'].isna().sum(axis=0))

# print(articles_df['title'].head(5))
# print(articles_df['title'].isnull().sum(axis=0))
# print(articles_df['title'].isna().sum(axis=0))

```

```

# print(articles_df['text'].head(5))

# print(articles_df['text'].isnull().sum(axis=0))

# print(articles_df['text'].isna().sum(axis=0))


# print(articles_df['lang'].unique())

# print(articles_df['lang'].isnull().sum(axis=0))

# print(articles_df['lang'].isna().sum(axis=0))


# Replace NaN with an empty string

# articles_df['text'] = articles_df['text'].fillna("")


articles_df = articles_df[articles_df['lang'] == 'en']

# print(articles_df.shape)


# return 0


# articles_df = pd.DataFrame(articles_df,
columns=['contentId', 'authorPersonId', 'content', 'lang'
# , 'title', 'text'
# ])


articles_df = pd.DataFrame(articles_df,
columns=['contentId', 'authorPersonId', 'content', 'title',
'text'])

```

```

# display(len(articles_df))

# display(articles_df.head(5))


# interactions_df = pd.DataFrame(interactions_df,
columns=['contentId',
'userCountry']).drop_duplicates(inplace=True)


# articles_df['contentId'] =
articles_df['contentId'].astype('int')

# interactions_df['contentId'] =
interactions_df['contentId'].astype('int')


# Merge keywords and credits into your main
metadata dataframe

# metadata =
articles_df.merge(interactions_df.set_index('contentId'
), on='contentId', how="inner")


# display(len(metadata))

# display(metadata.head())

# display(metadata.columns)


# return 0

# metadata.drop('timestamp', inplace=True, axis=1)

# metadata.drop('sessionId', inplace=True, axis=1)

```

```

# metadata.drop('userAgent', inplace=True, axis=1)

# metadata.drop('userRegion', inplace=True,
axis=1)

# metadata.drop('personId', inplace=True, axis=1)

# metadata.drop('content', inplace=True, axis=1)

# metadata.drop('eventType', inplace=True, axis=1)

# # metadata.drop('contentId', inplace=True,
axis=1)

# # display(metadata.columns)

# metadata.drop('authorPersonId', inplace=True,
axis=1)

# metadata.dropna(subset=["userCountry"],
inplace=True)


# display(metadata.columns)

# display(metadata.head(5))

# return 0


# features = ['text']

# display(metadata.columns)


# for feature in features:

#     metadata[feature] =
metadata[feature].apply(literal_eval)

```

```

# metadata['soup'] = metadata.apply(create_soup,
axis=1)

articles_df['soup'] = articles_df.apply(create_soup,
axis=1)

# display(metadata.head(5))

# display(metadata['soup'].head(5))

# display(metadata[['soup']].head(2))


# return 0


# display(metadata.head(10))


# Define a TF-IDF Vectorizer Object. Remove all
english stop words such as 'the', 'a'

tfidf = TfidfVectorizer(stop_words='english')


# Construct the required TF-IDF matrix by fitting
and transforming the data

tfidf_matrix = tfidf.fit_transform(articles_df['text'])


# Output the shape of tfidf_matrix

# print(tfidf_matrix.shape)

# print(tfidf.get_stop_words().pop())

```

```

# Array mapping from feature integer indices to
feature name.

# print(tfidf.get_feature_names()[5000:5010])

# count vectorize

# count = CountVectorizer(stop_words='english')

# count_matrix =
count.fit_transform(metadata['soup'])

# display(count_matrix.shape)

# return 0

# Compute the cosine similarity matrix

# cosine_sim = cosine_similarity(count_matrix,
count_matrix, True)

cosine_sim = cosine_similarity(tfidf_matrix,
tfidf_matrix, True)

# display(cosine_sim.shape)

# display(cosine_sim)

# Construct a reverse map of indices and movie
titles

# Reset index of your main DataFrame and
construct reverse mapping as before

```

```

metadata = articles_df.reset_index()

# indices = pd.Series(metadata.index,
index=metadata['title'])

indices = pd.Series(metadata.index,
index=metadata['title']).drop_duplicates()

# display(indices[:10])

# return 0

print(get_recommendations('The Rise And Growth
of Ethereum Gets Mainstream Coverage', indices,
cosine_sim,

                        metadata))

return 0

print(get_recommendations('Google Data Center
360° Tour', indices, cosine_sim,

                        metadata))

# return 0

print(get_recommendations('Intel's internal IoT
platform for real-time enterprise analytics', indices,
cosine_sim

                        , metadata))

```

```
return 0
```

```
def create_soup(x):  
    soup = ' '.join(x['text'])  
    return soup
```

SCREEN SHOTS:

The first screenshot shows a Jupyter Notebook with the following code in cell [25]:

```
metadata = articles_df.reset_index()
indices = pd.Series(metadata.index, index=metadata['title']).drop_duplicates()
display(indices[:10])
```

The output of the code is a list of 10 article titles:

```
title
0    Ethereum, a Virtual Currency, Enables Transactions That Rival Bitcoin's
1    Bitcoin Future: When GDPcoin of Branson Wins Over USDcoin of Trump
2    Google Data Center 360° Tour
3    IBM wants to "Evolve the Internet" With Blockchain Technology
4    IEEE to Talk Blockchain at Cloud Computing Oxford-Con - CoinDesk
5    Banks Need to Collaborate With Bitcoin and Fintech Developers
6    Blockchain Technology Could Put Bank Auditors Out of Work
7    Why Decentralized Conglomerates Will Scale Better than Bitcoin - Interview with Openledger CEO - Bitcoin News
8    The Rise And Growth of Ethereum Gets Mainstream Coverage
9    Setting up HTTP(S) load balancing
dtype: object
```

The second screenshot shows the same Jupyter Notebook with the following code in cell [26]:

```
def get_recommendations(title, indices, cosine_sim, data):
    idx = indices[title]

    sim_scores = list(sorted(cosine_sim[idx]))

    sim_scores = sorted(sim_scores, key=lambda x: x[1], reverse=True)

    sim_scores = sim_scores[1:11]
```

The output of the code is a list of 10 recommended article titles:

```
8    The Rise And Growth of Ethereum Gets Mainstream...
424    For Blockchain WTs, the Time for Ethereum Inve...
157    Ethereum and Bitcoin Are Market Leaders But Mo...
71    Microsoft Adds Ethereum to Windows Platform Fo...
94    Solidity Available in Visual Studio - Ethereum...
160    Microsoft Continues to Embrace Ethereum & Bitt...
97    Cashila Announces Consistent Buy and Sell Feat...
112    Eyeing Volume, Asian Exchanges Add Support for...
1701    Are you a bitcoin decentralist? - Chris Skinner's...
101    Decentralized Options Exchange Etheropt Uses A...
```

The output of the code is a list of 10 recommended article titles:

```
121    Google shares data center security and design ...
714    YouTube's New Messenger Means You'll Never Haw...
538    This year's founders' letter
207    Google Cloud Platform: The smart person's guid...
439    Top 5 GCP NEXT breakout sessions on YouTube (s...
699    Google I/O 2016 Preview: A Chrome/Android merg...
2059    [Tools] How to Record your Desktop Screen with...
708    Google I/O 2016 preview: Android N, Android VM...
756    Here's proof that Google is getting serious ab...
751    Google I/O 2016 Preview: Machine Learning, Vir...
```

```
In [26]: print(get_recommendations("Google Data Center security and design ...", indices, cosine_sim, metadata))

121 Google shares data center security and design ...
714 YouTube's New Messenger Means You'll Never Hav...
538 This year's founders' letter
287 Google Cloud Platform: the smart person's guide...
439 Top 5 GOP NEXT breakout sessions on YouTube (s...
699 Google I/O 2018 Preview: A Chrome/Android merg...
2058 [Tools] How to Record your Desktop Screen with...
708 Google I/O 2018 preview: Android N, Android M...
756 Here's proof that Google is getting serious ab...
751 Google I/O 2018 Preview: Machine Learning, Vir...
Name: title, dtype: object

In [27]: print(get_recommendations("The Rise And Growth of Ethereum Gets Mainstream Coverage", indices, cosine_sim, metadata))

0 Ethereum, a Virtual Currency, Enables Transact...
428 For Blockchain VC's, the flaw for Ethereum inve...
157 Ethereum and Bitcoin Are Market Leaders But No...
94 Solidity Available in Visual Studio - Ethereum...
71 Microsoft Adds Ethereum to Windows Platform Fu...
180 Microsoft Continues to Embrace Ethereum & Bli...
97 Cashila Announces Convenient Buy and Sell Feat...
112 Eyeing Volume, Asian Exchanges Add Support for...
181 Decentralized Options Exchange: Etheropt Uses A...
14 Five Bitcoin and Ethereum Based Projects to Wa...
Name: title, dtype: object
```

AI BASED NEWS RECOMMENDATION SYSTEM

MUKESS RAJAN .P

FINAL YEAR STUDENT (UG)

DEPARTMENT OF CSE

SATHYABAMA INSTITUTE OF
SCIENCE AND TECHNOLOGY

Mukessrandy711@gmail.com

MUSTAFA KADERDINA

FINAL YEAR STUDENT (UG)

DEPARTMENT OF CSE

SATHYABAMA INSTITUTE OF
SCIENCE AND TECHNOLOGY

mustikaderdina@gmail.com

Ms. BALASAI GAYATHRI

ASSISTANT PROFESSOR

DEPARTMENT OF CSE

SATHYABAMA INSTITUTE OF
SCIENCE AND TECHNOLOGY

balasaigayathri.cse@sathyabama.ac.in

ABSTRACT:

With the exponential growth of digital content and information sources, personalized news recommendation systems have become increasingly essential to cater to the diverse preferences and interests of individual users. This paper presents an AI based personalized news recommendation system that leverages machine learning techniques to deliver tailored news articles to users. The system uses a filtering method known as content based system and NLP model to provide relative and engaging news predictions. The primary objective of this recommendation system is to enhance user engagement with news content by delivering articles that align with their interests and preferences. The proposed AI-based personalized news recommendation system demonstrates promising results in terms of recommendation accuracy and the user

Interest By leveraging machine learning techniques, it effectively tailors news content to individual users, ultimately enhancing their news consumption experience. The system first utilizes TF-IDF to extract significant features from a large corpus of news articles , converting textual data into a vectorized format. Subsequently, to measure the resemblance between vectors cosine similarity is used, enabling the identification of articles most relevant to a user's interests. . This method can be effectively applied not only in news recommendation but also in other domains requiring personalized content delivery. This system, leveraging on ML and NLP techniques that has demonstrated a remarkable ability to provide users with highly relevant and personalized news content. The system can accurately predict and recommend news articles that align with individual interests, thereby

enhancing user engagement and satisfaction. We compare our AI-based, recommendation system's performance against traditional recommendation approaches. The results highlight a substantial improvement in the relevance and personalization of news articles recommended to users, as well as an increase in user engagement and satisfaction. The paper concludes with insights into potential future developments, including the exploration of real-time adaptive recommendations and the considerations of AI in content personalization in many other areas and to be more accurate and precise in future of content delivery systems and to prove the significance of artificial intelligence in the upcoming era of information .

INTRODUCTION:

In this era of rapid technological advancement and information explosion, The AI based News Recommendation System not only addresses the challenge of information overload but also redefines the way individuals interact with news. By using Artificial Intelligence and natural language processing it aim to provide users with a personalized and curated news experience tailored to their unique interests based on the previously searched articles and content relevance, the system ensures that users are presented with news articles

that align with their interest. The system's ability to predict based on user interactions in real-time enhances its accuracy, making the news consumption process not just efficient but also deeply engaging. The proposed AI based News Recommendation System represents a pivotal evolution in the way we navigate and engage with the world's vast amount of news content. By employing sophisticated machine learning techniques and AI-driven data analysis, The system not only caters to individual preferences but also anticipates and adapts, ensuring a dynamic and personalized news recommendation. We are committed to ensuring that the use of AI is harnessed ethically and responsibly, with a steadfast dedication to user privacy and data protection. By prioritizing these ethical considerations, our system insists confidence in users, fostering a sense of security in their data privacy. With an unwavering focus on user satisfaction, content relevance, and ethical standards, this paper is poised to improve the way individuals perceive and engage with news, ushering in a new era of informed, empowered, and personalized news consumption.

RELATED WORK:

1. "Personalized News Recommendation Based on Collaborative Filtering and Deep Learning" by Yifan Wang et al. (2018) - This paper proposes a personalized news

recommendation system that combines collaborative filtering with deep learning techniques. The study demonstrates the effectiveness of incorporating user behaviour data and content information to improve news recommendations.

2. "A Survey of News Recommendation and Analytics Systems" by T. Varghese et al. (2020) - This survey provides an overview of various news recommendation and analytics systems, including AI-based approaches.

3. "A Hybrid Collaborative Filtering Algorithm for News Recommendation" by X. Chen et al. (2019) - This research presents a hybrid collaborative filtering algorithm that combines user behavior and content features for news recommendation. The study shows how incorporating both types of data can lead to more accurate and diverse recommendations.

4. "Deep Learning for News Recommendation: An Autoencoder-Based Approach" by M. Zheng et al. (2017) - This paper explores the use of deep learning, specifically autoencoders, for news recommendation. The study shows how the autoencoder-based approach can capture complex patterns in user behaviour data and generate personalized news recommendations.

5. "A Contextual Bandit Approach to Personalized News Article Recommendation" by J. Li et al. (2018) - The research focuses on utilizing user context to dynamically update recommendations and improve user engagement.

6. "Personalized News Recommendation using Attention-based Hybrid Neural Network" by S. Kumar et al. (2019) - By incorporating user and article embeddings, the model effectively captures user

preferences and delivers personalized news articles.

7. "Fairness in News Recommendation: Unintended Bias and Potential Remedies" by A. Goel et al. (2019) - This paper examines the issue of unintended bias in news recommendation systems and proposes potential remedies to mitigate bias. The research addresses the ethical implications of personalized news recommendations and fairness in content delivery.

8. "User Privacy in News Recommendation Systems: A Survey" by N. Arif et al. (2021) - This survey explores the challenges and techniques related to user privacy in news recommendation systems. It discusses different privacy-preserving methods and their impact on the accuracy of personalized recommendations.

9. "Recurrent neural networks for news personalization with long and short term user context" by L. Wang et al. (2018) - This research investigates the use of the recurrent neural networks to user context for news personalization. The study demonstrates how considering user behavior over time improves the relevance of recommended news articles.

10. "Survey of News Recommendation Systems: Algorithms, Evaluation, and Future Work" by C. Luo et al. (2020)

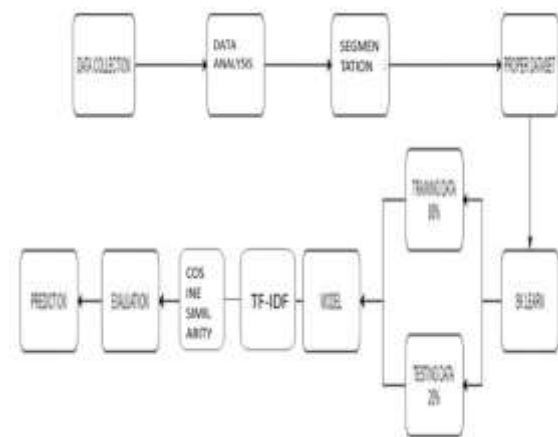
The Impact of Online Reputation on Consumer Purchase Decisions: A Review of the Literature by *Frontiers in Psychology* (2022). This comprehensive survey covers a wide range of news recommendation algorithms, including AI-based approaches. It provides insights into evaluation metrics, datasets, and future

research directions for news recommendation systems. These literature references offer valuable insights into the advancements, challenges, and state-of-the-art techniques in AI-based news recommendation systems

LITERATURE REVIEW:

AUTHOR	YEAR OF PUBLICATION	DESCRIPTIONS	Methodology
<u>Yifan wang</u>	2018	Personalized news recommendation based on deep learning	Used multiple Collaborative filtering
<u>X.chen</u>	2019	Hybrid collaborative filtering algorithm for News recommendation	Uses algorithm to find user behaviour
<u>M.zheng</u>	2017	Deep learning for news recommendation.	An automated encoder based approach
<u>S.kumar</u>	2019	News recommendation using attention based hybrid neural network	Using neural network
<u>Ngheip</u>	2001	A comparison of multiple regression analysis and artificial neural networks	Used SVM instead of linear regression
<u>L.wang</u>	2018	Recurrent neural network for News personalization	Used long and short term user context

ARCHITECTURE DIAGRAM:



METHODOLOGY:

Methodologies for The AI based news recommendation involve a systematic approach and the purpose of the research is to enumerate accurate recommendation content based model.

1.DATA COLLECTION:

Gathering diverse and comprehensive news data from reliable sources, including headlines, articles, categories, authors, publication dates, and user interactions To Ensure the data is representative of the target audience and covers a wide range of topics. In the development of an AI-based news recommendation system, the data collection phase is crucial. This stage involves gathering a diverse and comprehensive set of news articles from various sources. Typically, this includes major news outlets, niche blogs, and other relevant platforms. The data should

encompass not only the text of the articles but also essential metadata such as titles, publication dates, authors, and categories like politics, technology, or sports.

2.DATA ANALYSIS AND SEGMENTATION:

The data analysis and segmentation phase play a pivotal role in understanding user behaviour and content preferences. Each data element - timestamp, event type, content ID, author person ID, author session ID, author user agent, author country, title, text, and language - offers unique insights and contributes to the feature extraction.

Timestamp: This data point is crucial for analysing user engagement patterns. By segmenting data based on timestamps, it can identify peak reading times, understand how preferences change over different times of the day or week, and even detect seasonal trends in news consumption.

Event Type: Differentiating between event types such as views, clicks, shares, or likes provides a multi-dimensional view of user engagement. For instance, Segmenting articles by event type helps in understanding the varying levels of user interest and interaction with the news content.

Content ID: Each piece of news content can be uniquely identified with a content ID. By analysing user interactions with specific content IDs, the system can track the popularity of articles and identify trends in user preferences. This also assists in content-based filtering, where similar

articles are recommended based on previously interacted content.

Author Person ID and Author Session ID: These identifiers help in tracking the different individual authors and sessions. Analysing author person IDs can reveal which author wrote the article, while author session IDs can provide insights into specific app or website sessions of authors.

Author User Agent and Author Country: The user agent data offers insights into the devices and browsers used by content creators, which can be crucial for optimizing content presentation. Author country data aids in understanding geographical preferences and language, enabling the recommendation system to cater to regional tastes and languages.

Title and Text: The analysis of titles and text is a cornerstone of content understanding. Natural language processing techniques and keyword extraction applied to titles and text help in categorizing content and understanding underlying themes and sentiments. This analysis is vital for recommending articles that align with the user's interests.

Language: Segmenting content by language is vital for personalization, especially in multilingual user bases. By understanding the language preferences of each user, the system can ensure that recommendations are linguistically accessible, enhancing user engagement and satisfaction. Through the detailed analysis and segmentation of these data elements The recommendation system can

gain a comprehensive understanding of both user behaviour and content characteristics. This deep insight is what powers the system's ability to deliver personalized, relevant, and engaging news article recommendations.

3.FEATURE EXTRACTION

We are Using TF-IDF to convert the pre processed text into a numerical format and converting it into vectors. TF-IDF reflects the remarkableness of a word in a corpus, balancing the words frequency in the documents against its frequency in the corpus. We will create a matrix where each column represents a term from the total vocabulary, which is made up of all the words that are present in at least one article. Every column denotes a distinct article (title).

The frequency with which a word occurs in an article is determined by the TF-IDF score; however, this frequency is modified by the quantity of documents in which the word appears. The purpose of this adjustment is to reduce the weight of words that are commonly used in plot summaries and, as a result, their impact in calculating the final similarity score. Every term (word) in a document is given a weight by TF-IDF based on its inverse document frequency (IDF) and term frequency (TF).

$$TF(i, j) = \frac{\text{Number of times word } i \text{ appears in document } j}{\text{Number of words in document } j}$$

$$IDF(i, D) = \log \left(\frac{\text{Number of documents in the corpus } D}{\text{Number of documents containing word } i} \right)$$

$$weight(i, j) = TF(i, j) * IDF(i, D)$$

We will utilize scikit-learn, which provides an integrated TFIDF vectorizer class that generates a TFI-DF matrix. With the word vector prepared, we can now determine the similarities between articles based on their words. Various techniques exist for finding similarities, but cosine similarity is the most suitable approach. It evaluates the angle between two words to assess similarity, rather than just their geographic distance when plotted on a dimensional graph. As mentioned earlier, cosine similarity is unaffected by magnitude and is relatively simple and efficient to calculate (particularly when combined with TF-IDF scores).

$$\cos(\mathbf{x}, \mathbf{y}) = \frac{\mathbf{x} \cdot \mathbf{y}^T}{\|\mathbf{x}\| \cdot \|\mathbf{y}\|} = \frac{\sum_{i=1}^n x_i \cdot y_i}{\sqrt{\sum_{i=1}^n (x_i)^2} \sqrt{\sum_{i=1}^n (y_i)^2}}$$

The vector shape and sample values can be obtained by utilizing the sklearn library's cosine_similarity() method.

```
(2211, 2211)
array([[1., 0.02842853, 0.01414884, ..., 0.04717828, 0.08436331,
        0.01859574],
       [0.02842853, 1., 0.02096081, ..., 0.0256655, 0.03187741,
        0.01120014],
       [0.01414884, 0.02096081, 1., ..., 0.02092281, 0.04240744,
        0.],
       ...,
       [0.04717828, 0.0256655, 0.02092281, ..., 1., 0.05457163,
        0.07645089],
       [0.08436331, 0.03187741, 0.04240744, ..., 0.05457163, 1.,
        0.03965418],
       [0.01859574, 0.01120014, 0., ..., 0.07645089, 0.03965418,
        1., ...]])
```

The cosine similarity method compares each pair of vectors and calculates the cosine angle between them. The smaller

the angle, the more similar the elements are to each other. The values range from 0 to 1. In this particular case, there are matrices of size 2.2k by 2.2, with values that range from 0 to 1.

The completion of the similarity vector is now finished. Our next task involves creating a reverse map of indices using the indices of the 'title' field. Additionally, we should eliminate any duplicate titles that may be present.

```

title
Ethereum, a Virtual Currency, Enables Transactions That Rival Bitcoin's
Bitcoin Future: When BBPcoin of Branson Hits Over USDcoin of Trump
Google Data Center 360° Tour
IBM wants to "Evolve the Internet" With Blockchain Technology
IEEE to Talk Blockchain at Cloud Computing Oxford-Con - CoinDesk
Banks Need to Collaborate With Bitcoin and Fintech Developers
Blockchain Technology Could Put Bank Auditors Out of Work
Why Decentralized Conglomerates Will Scale Better than Bitcoin - Interview with OpenLedger CEO - Bitcoin News
The Rise And Growth of Ethereum Gets Mainstream Coverage
Setting Up HTTP(S) Load Balancing
dtype: object

```

Now that the indices are prepared, we can proceed to create the recommender system using the maps and matrices. To accomplish this, the simplicity function takes the title of the article as input, along with the indices (which contain the titles and their corresponding indices), the cosine similarity matrix, and the original dataset. Firstly, it identifies the index of the input title. In order to remove it later on, it iterates through the length of the cosine similarity matrix and assesses the distance of the articles from the input article that was provided. Subsequently, the articles are sorted based on their

similarity values, with the highest values appearing first. Finally, only the top 10 articles that exhibit the highest similarity thresholds are selected.

4.RECOMMENDATION

GENERATION: The articles are ranked according to their cosine similarity ratings and then displayed as recommendations to the user. A list of the top ten related articles is generated, and article names that match the indices from the previous step are returned.

RESULT:

Now we will see the result of the recommendation system with various input titles. Here, the input is users already read articles .So, the recommender will recommend based on the similarity of that article.

```

In [14]: print(get_recommendations('Google Data Center 360° Tour', indices, cosine_sim,
                                     metadata))

121  Google shares data center security and design ...
714  YouTube's New Messenger Means You'll Never Hav...
538  This year's Founders' Letter
207  Google Cloud Platform: The smart person's guid...
439  Top 5 GCP NEXT breakout sessions on YouTube (s...
699  Google I/O 2016 Preview: A Chrome/Android merg...
2099 [Tools] How to Record your Desktop Screen with...
748  Google I/O 2016 preview: Android N, Android M...
756  Here's proof that Google is getting serious ab...
751  Google I/O 2016 Preview: Machine Learning, Vir...
Name: title, dtype: object

```

As we can see it has found similar articles to google. It has also shows article that is related to youtube and doesn't have google in it. So evidently, the recommender system can detect the variants of a the article that is related. lets also try another

input to check whether the results are as good as the first one

```
In [18]: print(get_recommendations("Bitcoin wallets as Swiss Bank Accounts: The Developer's Perspective", indices, cosine_sim, metadata))

1781 Are you a Bitcoin dev? - Chris Skinner's...
153 Panama Papers Scandal Shows How Bitcoin Could ...
276 Our Goal is to Replace Your Need for a Bank, S...
156 Blockchain CEO's Business Advice on Bitcoin St...
99 Growing Global Electricity Consumption Is Not ...
96 Governments vs Bitcoin: A Fight For Control
25 French Senate Will Debate on Bitcoin Regulation
96 Bitcoin Launches to Solve Bitcoin Biggest Issues...
1852 What Apple's differential privacy means for yo...
307 Blockchain won't kill banks: Bitcoin pioneer
Name: title, dtype: object
```

So again the recommender system has returned a list of articles which has a range of articles related to etherium and bitcoin. so as we can see it concludes that the recommender systems recommends highly related articles as seen in the above two pictures .

SUMMARY:

The research paper explores the realm of AI-based news recommendation systems, the proposed system focus to deliver personalized news content to users. The Key methodologies include content-based filtering, where articles are recommended based on their similarity to previously read content. It approaches in a content-based systems that use of TF-IDF for extracting feature from the articles. This method effectively personalizes content by matching the thematic and topical interests of users with the available articles.

However, challenges such as inability to perform in real time is a major limitation however Continuous improvements and innovations in these systems are crucial for enhancing user engagement and providing a more enriched and diverse news consumption experience.

CONCLUSION:

In conclusion, an AI-based news recommendation system represents a significant advancement in the way users interact with news content. By leveraging sophisticated algorithms and machine learning techniques, these systems are able to analyse large volumes of data, learning from user interactions and preferences to provide personalized content that is more relevant and engaging. This not only enhances the user experience by filtering out irrelevant information but also helps in discovering new topics and perspectives. Furthermore, such systems have the potential to increase user engagement and retention for news platforms, as they deliver content that aligns closely with individual interests. Despite their successes, these systems face several challenges and limitations. Additionally, the reliance on textual content analysis can lead to an incomplete understanding of user preferences, as it may not fully capture the nuances of user behaviour or the contextual significance of multimedia

elements in news articles. Looking ahead, future research in this field holds immense potential. Enhancements could include integrating multimodal analysis, which considers visual and audio elements alongside text, and incorporating real-time feedback mechanisms to adapt recommendations dynamically. In summary, while AI-based news recommendation systems have made significant strides in personalizing content delivery, continuous innovation and research are essential for overcoming current limitations and fulfilling the potential of these technologies in shaping how users interact with news content. The AI-based news recommendation systems have a promising future, with ample scope for innovation and improvement in providing personalized, diverse, and insightful news content to users worldwide.

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CERTIFICATE

