Enhancing Personalized News Recommendations with a Hybrid Model: Integrating BERT, Neural Collaborative Filtering and Attention Mechanisms

MSc Research Project
MSc Data Analytics

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MSc Project Submission Sheet

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Programme:	MSc Data Analytics **Year:** 2024
Module:	MSc Research Project
Supervisor:	Musfira Jilani
Submission Due Date:	12/12/2024
Project Title:	Enhancing Personalized News Recommendations with a Hybrid Model: Integrating BERT, Neural Collaborative Filtering and Attention Mechanisms
Word Count:	7847
Page Count:	22

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Enhancing Personalized News Recommendations with a Hybrid Model: Integrating BERT, Neural Collaborative Filtering and Attention Mechanisms

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Abstract

Personalized news recommendation systems are pivotal in addressing the growing demand for relevant and engaging content. This research explores a hybrid recommendation model combining BERT based content embeddings, Neural Collaborative Filtering (NCF) and an attention mechanism to enhance the accuracy and relevance of news recommendations. The study utilizes the MIND dataset which provides a rich collection of user interactions, news metadata and pre-trained entity embeddings. The proposed model leverages BERT to extract contextual embeddings from news content and NCF to model user-item interactions. An attention mechanism is integrated to prioritize key interactions allowing the system to tailor recommendations based on user behaviour. Through rigorous experimentation, the model is evaluated using metrics such as precision, recall and normalized discounted cumulative gain (NDCG). Findings reveal that the hybrid approach significantly outperforms baseline models, demonstrating improved precision and user satisfaction in recommendations. However, challenges such as overfitting in high dimensional embeddings and computational complexity were identified. Regularization techniques like dropout and L2 regulations were employed to address these issues effectively. The study contributes to the growing body of research in personalized news recommendation systems by integrating advanced NLP and recommendation techniques. Future work will focus on incorporating additional contextual factors example temporal and geographic preferences, exploring lightweight alternatives for real-time deployment. These advancement hold promise for more accurate, scalable and user centric news recommendation systems.

1 Introduction

In today's information rich modern world, the personalized news recommendation systems have become very crucial in helping the users to navigate through massive amounts of digital content. Based on the individual's preference these systems are designed to filter, prioritize and deliver news articles. Traditional methods like collaborative filtering or content-based filtering for recommendation system which face lot of challenges when applied in a fast-changing areas like news, where the importance of content changes quickly and is unique to each user. Recent advancement in hybrid recommendation systems which combines both content and collaborative filtering shows great potential in the fields like e-commerce and video streaming. But the application of these hybrid methods in news recommendations is still unexplored, particularly when it comes to understanding the complex details of news content and user interactions. This project aims to improve the advanced NLP models like BERT (Bidirectional Encoder Representations from Transformers), for deep content analysis with Neural Collaborative Filtering (NCF) for user-item interactions, and an attention mechanism to dynamically prioritize critical content and interaction features. Together to build a hybrid recommendation system that can deliver more accurate personalized news recommendations.

Due to the growth of digital news platforms the importance of personalized news recommendation systems also increased. However, current recommendation system often does not have the ability to capture user interest with high precision. One major challenge is the complexity of the news articles, which has subtle and nuanced information. Traditional methods may not be able to process these details effectively. At the same time, user preferences may change frequently and can evolve quickly based on new interest or current events. Addressing these issues requires a more advanced approach that can better understand both the content of the article and the changing behaviour of each user. This project introduces a hybrid model that combines advanced tools to tackle these challenges. By using BERT a powerful natural language processing model, our system can deeply analyse the content of news articles which includes the titles, abstracts, and categories, NCF captures the patterns in user interactions, such as which articles were clicked or ignored and attention mechanism enhances this by selectively weighting important features in both content and user interactions data ensuring that the most relevant aspects of news articles and behaviours are emphasized. These tools combined provides a rich understanding of both news content and user preferences. By combining these innovative techniques, the project aims to significantly improve accuracy and relevance of personalized news recommendations.

The factors that influence the outcome of the news recommendation models are the depth and richness of the textual data which includes news titles, abstracts and embedded entities, historical click behaviours and impression logs that provide insights into user preferences, user preferences for news topics that changes over time, impacting recommendation relevance, the ability to emphasize important features both in content and user interaction plays an important role in improving model accuracy.

The research question that we are going to investigate in this study: how can a hybrid recommendation model that combines BERT based content embeddings and NCF collaborative filtering signals and attention mechanism enhance personalized news recommendations?

To address the research question, we need to investigate the existing techniques in news recommendation and understand their limitations in dynamic news domains, develop a recommendation system that combines BERT embeddings for content analysis with NCF for user item interaction, and attention mechanism for feature prioritization and test the hybrid model on the mind dataset to assess the model’s effectiveness.

The major contribution of this research is a novel hybrid recommendation model that combines BERT and NCF with attention mechanism, leading to improved news recommendation system, particularly for large scale dataset like MIND (Microsoft News Dataset).

Structure of the Paper:

- **Section 2: Related Work** – A comprehensive review of existing recommendation techniques and hybrid approaches in the context of news recommendation.
- **Section 3: Research Methodology** – Detailed explanation of data preprocessing, feature extraction, model architecture, and the integration of BERT and NCF with attention mechanism.
- **Section 4: Experiment and Results** – Description of the experimental setup, evaluation metrics, and the performance analysis of the proposed model on the MIND dataset.
- **Section 5: Discussion** – Analysis of findings, including the model's strengths and limitations, and suggestions for future work.
- **Section 6: Conclusion** – Summary of key results and implications for future research in personalized news recommendation systems.

2 Related Work

2.1 Personalized News Recommendation using Hybrid Approaches

The field of personalized news recommendation systems has been significantly evolved over the years. A common challenge in this domain is effectively capturing user preferences and delivering content that aligns with their interests. Several studies have explored hybrid methods that combine content based and collaborative filtering approaches to improve recommendations accuracy. Wu et al. (2024) introduced the MIND dataset as a benchmark for news recommendations system. They demonstrated that the performance of these systems is highly dependent on the quality of news content understanding and user interest modelling. In their study, they highlighted the effectiveness of using pre trained language models like BERT for content representation showing that these models significantly improve news recommendation performance. However, a limitation of this approach is the reliance of click history for user behaviour. Li et al. (2023) also emphasized the need for better user modelling in news recommendation systems. They discussed the limitations of using click data as the sole indicator of user interest and suggested that incorporating other user behaviours such as web browsing history could provide more accurate model of user preferences. Additionally, they proposed integrating deep neural networks (DNN) with collaborative filtering methods to enhance recommendation accuracy. However, their model's complexity, particularly with incorporating temporal dynamics, may increase computational costs, which could be a drawback when scaling to large datasets. Liu (2024) proposed an LSTM based hybrid model that combines LSTM's ability to capture sequential dependencies with attention mechanism to focus on the most relevant aspects of user behaviour and news content. This approach effectively captures temporal context in user interactions, enhancing the accuracy of personalized recommendations. However, as with other deep learning models, LSTM based attention mechanism are computationally expensive and their training time increases as the model complexity grows. Additionally, while the attention mechanism improves focus on key features it can still struggle with understanding broader user interest across multiple domains.

2.2 Deep Learning and Attention Mechanism

Deep Learning methods particularly those utilizing neural networks like CNNs and RNNs, have been widely adopted to model user preferences in news recommendation systems. Yadav and Yadav. (2024) explored a collaborative filtering-based hybrid system, combining matrix factorization techniques with deep learning models. The use of deep learning (DL) methods such as CNNs helps in extracting richer feature representations from news content, while models like KNN provides better user-item interactions. However, while the combination of CNNs with matrix factorization models enhances the system's ability to infer latent features, it still faces challenges in incorporating temporal data or evolving user preferences over time. Similarly, the paper by Delvin et al. (2019) introduced BERT, a pre-trained bidirectional language model that can significantly improve the understanding of news content through contextual embeddings. BERT's ability to process both left and right contexts allows it to generate more accurate and meaningful representations of news articles, which are crucial for personalized recommendations. However, the computational cost of fine-tuning BERT, especially when applied to large scale datasets, remains a significant limitation. Furthermore, BERT does not inherently address user behaviour modelling, which is critical component of personalized recommendations. As such combining BERT's embeddings with collaborative filtering models as done in hybrid systems, could be an effective solution to overcome this gap. An interesting approach was presented by the New York Times recommendation system, Petrusel, (2022) which was unsupervised clustering techniques such as k-means to group articles based on topics, followed by KNN for personalized recommendations. This approach is effectively in mitigating the problem of information overload by suggesting articles based on clusters of topics the user has previously shown interest in. However, the model's reliance on unsupervised learning limits its ability to capture complex user-item interactions, as it doesn't explicitly model user preferences on behaviours. The combination of deep learning with hybrid recommendation systems has proven effective in tackling the problem of personalized news recommendations. However, limitations persist in the model's complexity, scalability and their ability to fully incorporate user behaviour beyond clicks. While methods like LSTM based attention models and BERT embeddings improve content understanding and features extraction, collaborative filtering techniques still requires advancement to better address temporal dynamics and evolving user interests.

2.3 Summary and Research Gap:

In summary, while numerous methods have been proposed for personalized news recommendation systems, including BERT-based content modelling, LSTM based attention mechanisms and collaborative filtering, several key gaps remain. First, many systems still overly rely on click history or static user behaviour data, failing to adequately capture the dynamic nature of user preferences over time. Second, while deep learning techniques have enhanced content understanding, they often come at the cost of increased computational complexity and are not always scalable. Additionally, although unsupervised approaches like clustering provide valuable insights into user preferences, they do not fully address the need for explicit user interaction modelling. Thus, there is a clear need for hybrid recommendation models that combine BERT based embeddings, collaborative filtering and temporal dynamics to better capture the evolving nature of user interests. This would help overcome the limitations of existing approaches, making the system both more efficient and more accurate in providing personalized news recommendations.

3 Research Methodology

3.1 Overview of Personalized news recommendation system:

Personalized recommendation system is an intelligent framework designed to analyse user behaviour and preferences to deliver a tailored content or product suggestions. By utilizing historical data and behavioural patterns these systems aim to enhance the user's satisfaction and engagement, which makes this personalized recommendation system an essential in sectors like e-commerce, online media and streaming platforms. The core function of these systems lies in their ability to accurately predict user preferences by understanding and analysing user data. By understanding a user's behavioural habits, the system provides more precise and relevant recommendations, which:

- Enhance user satisfaction and retention.
- Encourages people to explore more content.
- Promotes efficient decision making by reducing the information overload.

Traditional methods in news recommendation systems suggested by Li, M. and Wang, L., 2019 are:

Collaborative filtering which relies on user interaction to recommend items. It works by finding similarities between users or contents. It struggles with a cold start problem (new users or new articles) and it limits its ability to recommend novel or diverse articles.

Content-based filtering which uses metadata like keywords, categories or tags from news articles to find matches based on a user's past interactions. It lacks in collaborative signals leading to recommendations that might be overly narrow and redundant.

These methods laid the foundation for recommendations systems, they are not equipped to handle the complexity and dynamics of modern news platforms.

Role of BERT:

BERT is a state of art NLP model that excels at capturing semantic relationships in text (Devlin et al.2019). It plays a crucial role in this project by understanding context where BERT analyses both the titles and abstracts of news articles bidirectionally ensuring a deep understanding of the content, high quality embeddings are created using BERT that represents each article's semantic meaning and these embeddings provide rich input features for the recommendation system, enabling more relevant suggestions. In this project BERT embeddings form the backbone of the content-based recommendation component creating meaningful representations of news content that work well with collaborative filtering data.

Neural Collaborative Filtering (NCF):

It leverages deep learning to capture the complex interactions between users and items in a recommendation system. It builds on a traditional collaborative filtering methods but enhances them with the flexibility and power of neural networks to capture non-linear relationships. The main goal of NCF is to predict a user's preference for a news article based on the past interactions. Instead of using simple similarity measures or matrix factorization as in traditional CF, NCF uses neural network to learn a more intricate representation of user-item relationship. To further enhance NCF, this project integrates an attention mechanism into the user-item interactions, emphasizing the most relevant aspects of past behaviour.

Why attention Matters:

User preferences often vary in importance across interactions. For example, certain articles may have a strong influence on future preferences. The attention mechanisms allow the model to focus on these significant interactions, leading to better personalized recommendations which was inspired by Liu, Y. and Gao, L., 2023. By combining the NCF's ability to model non-linear relationships with the attention mechanism's capabilities to prioritize critical features the system achieves a deeper understanding of user behaviour, improving prediction accuracy.

3.2 Methodology diagram:

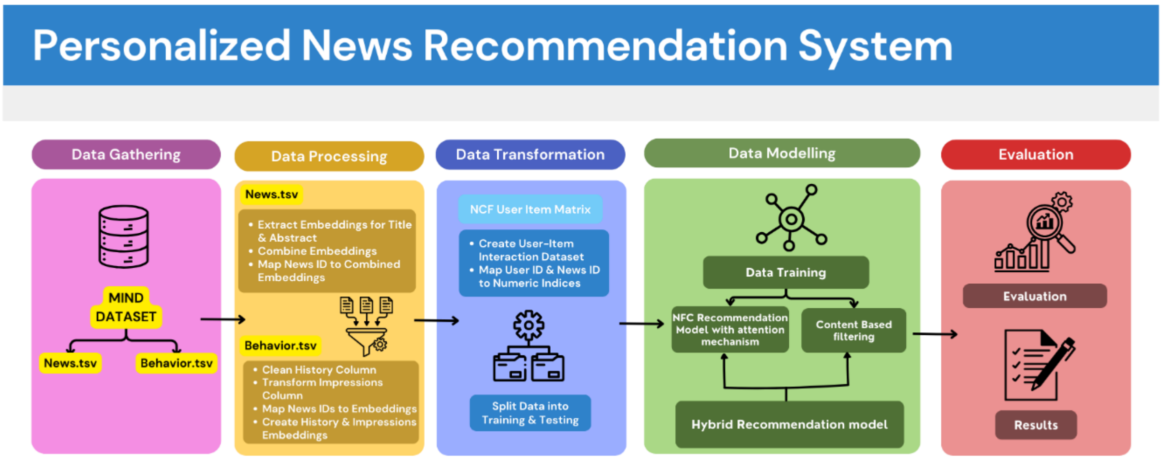

Figure 1: Methodology diagram

This project mains to build a hybrid recommendation system using the MIND (Microsoft News Dataset), combining BERT based content filtering and Neural collaborative filtering. The methodology of this project consists of five major steps:

Data Gathering:

For this project, the MIND dataset Wu et al. (2024) which is a large-scale dataset for news recommendation research is used. It was collected from anonymized behaviour logs of Microsoft news website. The data spans six weeks from October 12 to November 22 of 2019. A total of 1 million users who had at least 5 new clicks during the period were sampled. For MIND-small dataset a subset of 50000 users and their behaviour logs were randomly selected. To ensure user's privacy all the user IDs were securely hashed into anonymized IDs and de-linked from production systems. We have two datasets from MIND-small News.tsv and Behaviors.tsv.

Behavior.tsv:

The behavior.tsv contains the clicks histories and impression logs of users. It has five columns namely,

Columns	Data Description
Impression ID	The ID of an impression
User ID	The anonymous ID of a user
Time	The impression time with format "MM/DD/YYYY HH:MM:SS AM/PM"
History	the new click history of the user before the impression. The clicked news articles are ordered by time
Impressions	list of news displayed in this impression and user's click behaviours on them (1 for click and 0 for non-click). The order of news in an impression have been shuffled.

An Example is shown in the table below:

Columns	Contents
Impression ID	91
User ID	U397059
Time	11/15/2019 10:22:32 AM
History	N106403 N71977 N97080 N102132 N97212 N121652
Impressions	N129416-0 N26703-1 N120089-1 N53018-0 N89764-0 N91737-0 N29160-0

News.tsv:

This News.tsv contains the detailed information of news articles involved in the behaviors.tsv file. It has 7 columns namely,

Columns	Data Descriptions
News ID	ID of the news
Category	Category of the news
SubCategory	Subcategory of the news
Title	Title of the news
Abstract	Abstract of the news
URL	URLs have expired now
Title Entities	Entities contained in the title of this news
Abstract Entities	Entities contained in the abstract of this news

An Example is shown in the table below:

Columns	Contents
News ID	N37378
Category	sports
SubCategory	golf
Title	PGA Tour winners
Abstract	A gallery of recent winners on the PGA Tour.
URL	https://www.msn.com/en-us/sports/golf/pga-tour-winners/ss-AAjnQjj?ocid=chopendata
Title Entities	[{"Label": "PGA Tour", "Type": "O", "WikidataId": "Q910409", "Confidence": 1.0, "OccurrenceOffsets": [0], "SurfaceForms": ["PGA Tour"]}]
Abstract Entities	[{"Label": "PGA Tour", "Type": "O", "WikidataId": "Q910409", "Confidence": 1.0, "OccurrenceOffsets": [35], "SurfaceForms": ["PGA Tour"]}]

Data Processing:

Using drive.mount(), the Google Drive is mounted, enabling access to files stored in the user's Drive. Two primary datasets, the news.tsv and behaviors.tsv are loaded into Pandas Dataframes.

For news.tsv:

A pre-trained BERT model (Bert-Base-Uncased) is loaded to extract meaningful features from text as tokenizer. The function get_bert_embedding() takes text input (the title and abstract from news.tsv), converts it into tokens using BERT's tokenizer, and processes it through the model to get numerical representation called embeddings. To simplify, it averages the output from BERT's last layer into a 768-dimensional vector. If the input text (title or abstract) is empty or invalid, the function returns a zero vector instead. These embeddings help represent text for machines to understand. For each news articles title embeddings and abstract embeddings are computed to the respective text columns by get_bert_embedding() function. A combined embeddings is calculated by averaging the title and abstract embeddings using numpy.mean(). This gives a single representation of the news article that captures information from both the title and the abstract. The updated dataframe with title, abstract and combined embeddings is saved as news_with_embeddings.csv.

For behaviors.tsv:

- **Processing history Column:**
  The history column in the behaviors.tsv dataset contains a list of news articles that a user has previously interacted with. The goal is to clean and standardize this data to ensure it can be used effectively. First step is to handle missing values any null values present in the history columns are replaced with empty strings. This ensures that missing values do not cause issues during processing. Additionally, each history entry is split into individual news_id. Extra characters like brackets [] or commas are removed from these IDs to keep them clean. A lambda function is applied to ensure that all valid entries in the column are transformed into lists of clean news_ids.

- **Processing Impressions Column:**
  The impression column lists news articles shown to users during a session along with binary label indicating whether each article was clicked (1) or not (0). The goal is to parse this information into structured format. A function process_impressions() is defined to split each impression string into tuples of (news_id, click_label). Additionally, another function is applied to the impressions column using .apply(), if an entry is not a string then it is replaced with an empty list [].

- **Creating Dictionary:**
  Each news article is represented by a combined embedding derived from its title and abstract. The goal is to create a dictionary that maps each news_id to its corresponding embeddings for fast lookup. a dictionary news_embeddings_dict is created using python's dict() function. The zip() function pairs each news_id with its corresponding combined embedding from the news_with_embeddings dataframe.

- **Mapping Embeddings for history and impressions:**
  A function map_history_to_embeddings() is defined to iterate through a list of news_ids. For each news_id the function retrieves its embedding from the dictionary. If the news_id is not found in the dictionary, a zero vector of length 768 is returned as a placeholder. The function is applied to the history column using apply(). Generating a new column history_embeddings. Similarly, a function map_impressions_to_embeddings() is defined to process a list of impressions. Each tuple (news_id, click_lable), the function retrieves the embeddings for the news_id and pairs it with the click_label. The function is applied to the impressions_processed column, creating a new column impressions_embeddings.

Data Transformation:

- **Create User-Item Interaction Dataset:**
  The dataframe behaviors_df contains user interactions in the form of impression logs. Each row includes the user ID, a timestamp, and the impressions which is a list of news items the user viewed along with click labels (1 if clicked, 0 if not). Each user's impressions are processed to extract individual interactions. Each impression is a tuple consisting of news_id and a click_label. For example, if a user viewed three news articles, the row is expanded into three interactions, one for each article, along with its click lable. The processed data is then stored in a new list user_item_interactions. Each entry in this list represents a specific interations. After processing all the rows the list of interactions is converted into a structured dataframe. This produces a tabular dataset where each row is a single user-item interaction, which is essential for training the NCF model.

- **Map User Ids and News Ids to Numerical Indices:**
  To effectively train the models like NCF, categorical identifiers such as user IDs and news IDs must be converted into numeric indices. New columns, user_index and news_index are added to the interaction_df. These columns contain the numeric indices corresponding to the user_id and news_id respectively. This transformation creates a clean, numeric representation of the data which is now ready for feeding into NCF model.

- **Split Data into Training and Testing Sets:**
  To evaluate the model's performance, the data is split into training and testing sets. The train_test_split function is used to split the data, the test_size is 0.2 parameter specifies that 20% of the data is set for testing, while the remaining 80% is used for training. The random_state= 42 parameter ensures that reproducibility of the split, where same data split is produced every time, the code is run.

Data Modelling:

- **Neural collaborative Filtering:**
  The inputs are user_input and news_input which represents a single user and news article as a numeric index respectively. Maps user and news Id to dense vector representations in a latent space. These embeddings capture meaningful relationship between user and items such as preferences and item similarities. Combining the user and news embeddings into a single feature vector, representing interaction between a user and article. After generating embeddings for users and news articles an attention layer is applied. The attention mechanism identifies the most important interactions by assigning weights to the embeddings based on relevance. For instance, certain user behaviours like clicking on a trending article may carry more weight in predicting future interactions. Attention scores are computed for each interaction in a user's history. These scores are used to scale the user-item embeddings before concatenation, ensuring the model focuses on the most relevant features. A sequence of dense layers refines the concatenated embeddings, capturing complex relationships. Dropout layers prevent overfitting by randomly disabling nodes during training. The output layer predicts a single value using a sigmoid activation representing the probability of the user clicking on the news article. The trained NCF model is evaluated on the test dataset using metrics like loss and accuracy which measures its ability to predict user clicks on unseen data. For a given user, identify news articles the user hasn't interacted with, predict the probability of the user clicking on each unviewed article return the top-N articles with highest predicted probabilities.

- **Content-Based Filtering:**
  To recommend similar news articles based on the content of a given article (title, abstract). Each article is derived from its title and abstract these embeddings are precomputed and stored in the news_with_embeddings dataset. The embeddings of the given news article is compared with all other article embeddings using cosine similarity. Cosine similarity measures the angle between two vectors capturing their relative similarity. Higher score of similarity indicates greater relevance between articles. The articles are ranked based on similarity scores. The top-N articles excluding the input article are returned as recommendations along with metadata like title, URL, etc.

- **Hybrid Recommendation System:**
  To combine the strengths of NCF (User Preferences) and content-based filtering (article similarities) for personalized, diversified recommendations. Collaborative recommendation where the trained NCF model recommend articles based on the user's historical preferences and content-based recommendations where find articles similar to the given news_id based on cosine similarity of embeddings, combining these two recommendations for producing a hybrid recommendation system. The results from both the methods are concatenated into a single dataset, enduring no duplicates. The

final output is a list of articles personalized for the user and enriched with content - based similarities.

4 Design Specification

The framework and tools for this personalized news recommendation system leverage advanced programming environments, libraries and hardware to ensure efficient development and deployment. The implementation is carried out in python, a versatile language widely used in machine learning and data science. For the deep learning components such as Neural collaborative filtering (NCF) and attention mechanism, frameworks like TensorFlow or PyTorch are employed. These libraries provide robust APIs for building and training complex neural network architectures. For the content embedding process, the hugging face transformers library is utilized to integrate a pre-trained BERT model, enabling the extraction of high-quality semantic embeddings from news articles. Additionally, Scikit-learn is used for critical task like data preprocessing, model evaluation, computing performance metrics, ensuring a streamlined workflow. The dataset used for this project is the Microsoft News Dataset (MIND), a comprehensive and large-scale dataset designed for news recommendation research. Its rich content, including user click behaviours, impression logs and detailed article metadata serves as the foundation for training and testing the recommendation system. Given the computational demands of processing large datasets and training deep learning models, hardware requirements include a GPU to accelerate model training, especially for tasks involving BERT and NCF and a high memory system to efficiently handle large-scale MIND dataset. These tools and infrastructure collectively support the development of an advanced, scalable and efficient hybrid recommendation system.

The system leverages a hybrid recommendation approach that combines the strengths of content based filtering and collaborative filtering. The architecture integrates advanced NLP and deep learning techniques, ensuring a personalized and accurate recommendation experience for users.

The key components of the personalized news recommendation system are designed to integrate advanced machine learning techniques and scalable data handling strategies.
The **data Preprocessing and transformation** step focuses on preparing and formatting the raw user interaction data and news content for model training. This involves extracting user-item interactions data from impressions logs, mapping categorical identifiers (like user_id and news_id) to numerical indices for embedding generation and splitting the data into training and testing sets to evaluate model performance. Efficient handling of large-scale datasets, such as MIND is critical for ensuring scalability and performance.

The **content embedding using BERT** component employs a pre trained BERT model to generate high quality embeddings for news articles, capturing their semantic meaning based on titles, abstract and categories, an example model is in figure 2 from Devlin et al. (2019). The [CLS] token output from BERT represents the overall semantic context of each article. These embeddings are precomputed and stored for fast similarity computations during inference, requiring GPU access for efficient processing of large datasets.

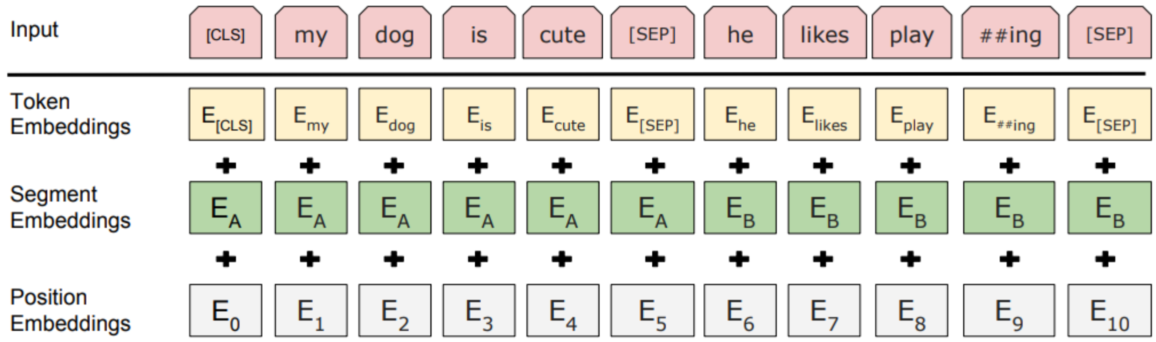

Figure 2: BERT input representation by Devlin et al. (2019)

The **Neural Collaborative Filtering (NCF)** module models user preferences by analysing historical interactions with news articles. It learns user-item interaction through embeddings that capture the underlying relationship between users and items. To enhance this process an attention mechanism is incorporated to prioritize significant user-item interactions, assigning weights that emphasize relevant interactions. These embeddings are passed through a dense layer to model complex, nonlinear relationships. Robust computational resources are required to tarin this deep learning based model effectively.

The **attention mechanism** plays a major role in improving the interpretability and performance of both the NCF and hybrid model, this is inspired by Liu, Y. and Gao, L., 2023. In the NCF model, it assigns weights to user-item embeddings before processing them through dense layers, ensuring that the model focuses on the most meaningful interactions. In the hybrid framework, the attention mechanism is applied to prioritize articles by combining score from collaborative and content-based recommendations, enabling the system to balance user preferences and article similarities dynamically.

Finally, **Hybrid recommendation** framework combines the strengths of NCF and content-based filtering to provide personalized, diverse and accurate recommendations. This involves merging ranked results from both methods and using an attention- weighted strategy to prioritize recommendations effectively. The framework ensures that duplicate recommendations are avoided and delivers results in real time, making the system adaptable and user-friendly. These components collectively enable the system to deliver precise and dynamic recommendations tailored to each user's evolving preferences.

5 Implementation

5.1 Data Preprocessing and Transformation:

The initial phase of the implementation focused on preparing and transforming the raw data to make it suitable for the recommendation system. The user interaction data, which is stored as impression logs in the Microsoft News dataset was processed as:

Extraction of User-Item Interactions:
The impression logs where each row in the log represents a user's engagement with a set of news articles were parsed to extract individual user-item interactions. The interactions were expanded and for each interaction a tuple containing the news_id and its corresponding click label (1 if clicked and 0 if not) was created.

Mapping User IDs and News IDs to Numerical Indices:
Since the recommendation model requires numeric inputs, the categorical data (user Id's and news Id's) was mapped to numerical indices. This transformation was necessary to create the embeddings that the model uses to represent users and news articles. The preprocessed data was split into training and testing data using 80-20 split. This ensures that the model can be evaluated on unseen data to test its generalization capabilities.

Tools used: Python, pandas for data manipulation and Scikit-learn for splitting the dataset.

Output: A clean, transformed dataset ready for training, containing user-item interactions, numeric mappings for users and news articles and split training and testing dataset.

5.2 Content Embedding Using BERT:

To represent the semantic content of the news articles, the BERT model was employed to generate high quality embeddings based on the article's titles and abstracts. The key steps in this process are:

Pre-trained BERT Model:
A pre trained version of BERT from hugging face transformers was used to generate embeddings. The article content, including titles and abstracts was tokenized and fed into BERT to generate contextual embeddings. The output of the [CLS] token was used as the semantic representation of the article. This embedding captures the overall context and meaning of each article, making it suitable for use in the recommendation system. The embeddings were stored in a dedicated dataset (news_with_embeddings), allowing for fast retrieval and comparison during the recommendation phase.

Tools Used: Hugging Face Transformer, BERT model, PyTorch for GPU- accelerated Processing.

Output: Precomputed semantic embeddings for each news article, stored for efficient similarity computation.

5.3 Neural Collaborative filtering:

This model was implemented to get the complex user-item interaction patterns. The key steps for implementing NCF are:

Embedding Layers:
Both users and news articles were represented as embeddings, where each user and news articles are mapped to a dense vector. These embeddings capture the relationships between users and items.

Attention mechanism:
To prioritize the most significant interactions the attention mechanism was applied to the user-item embeddings before they were passed through the dense layers. The attention mechanism assigns weights to the embeddings, highlighting more relevant historical interactions and improving model interpretability.

Model Architecture:
The user and news article embeddings were concatenated and passed through a series of dense layers, enabling the model to learn non-linear relationships between users and articles. Dropout layers were used to prevent overfitting during training. The NCF model was trained on the user-item interaction data with the output being predicted probability of whether user click on a specific news article.

Evaluation:
The model was evaluated using standard metrics such as loss, accuracy and AUC to measure its ability to predict user interactions with unseen data.

Output: A trained NCF model capable of predicting user preferences based on past interactions.

5.4 Hybrid Recommendation System:

To Combine the benefits of both Neural collaborative filtering (with attention mechanism) and Content based filtering (via BERT embeddings), a hybrid recommendation system was developed. This hybrid approach ensures that recommendations are both personalized and diverse. The recommendations from both the NCF and content-based filtering were merged. A weighted sum approach was used, where the scores from both the models were combined, ensuring that both user preferences and content relevance were considered. Duplicate articles were removed to ensure that users did not receive the same article from both the models, providing cleaner and more diverse recommendations.

Output: A hybrid recommendation system that integrates both content-based and neural collaborative filtering results with attention- weighted mechanism for prioritizing top recommendations.

5.5 Final System Output:

The final output of the system is a personalized list of articles for each user. This list is generated based on **both collaborative filtering and content- based filtering with** an attention mechanism ensuring that the most relevant articles are prioritized. The results are returned to the user, offering tailored recommendations that are both diverse and highly relevant. The model's performance was tested on the test dataset, and results were compared with baseline models to assess the improvement gained by using a hybrid system with attention mechanism.

6 Evaluation

A comprehensive analysis of the results from the three recommendation models – Neural Collaborative filtering with attention mechanism, content-based filtering using BERT and the Hybrid model is used to generate personalized news recommendations. These models are evaluated using Precision@K, Recall@K, NDCG@K. The goal was to assess the ability of these models to provide relevant personalized recommendations to users based on their interaction history and the content of news articles. The results of each model are discussed below, and the implications of these findings are explored from both academic and practical perspectives.

6.1 NCF with Attention Mechanism Model Results:

The NCF model, focuses on learning the interactions between users and news articles was evaluated over 10 epochs. The dataset was split into training and testing subsets with a portion of the training data reserved for validation. The model was trained for 10 epochs using binary cross entropy loss and the Adam optimizer. Metrics like accuracy and loss were monitored during training to ensure steady learning and prevent overfitting. The model incorporates embedding layers to represent users and articles, dense layer for interaction learning and an attention mechanism to prioritize the most relevant features. The model achieved 96.19% training accuracy by the 10^{th} epoch, indicating a strong fit to the training data, validation accuracy reached 95.72 showing reasonable generalization to unseen data. Progressively decreased from 0.1686 to 0.1482 over 10 epochs, demonstrating effective optimization and learning. The evaluation metrics for a random user U91836 Produced Precision@K as 0.60 – 60% of the recommended top-K articles were relevant to the user, Recall@K as 0.43, the model retrieved 43% of all the relevant articles for the articles for the user, NDCG@K as 0.55, where the ranking of recommendations was moderately aligned with user preferences and AUC as 0.84 indicating a strong performance in ranking clicked articles above non-clicked ones. The high precision and AUC indicate the model's ability to rank relevant articles effectively. The inclusion of the attention mechanism helped the model prioritize critical features, improving its predictive capabilities but a Recall@K of 0.43 suggests the model misses some relevant articles, limiting its ability to retrieve all user-preferred content. The model's reliance on historical interaction data may challenge its effectiveness for new users or articles (Cold Start Problem).

Method	Evaluating Indicator		
	P	R	F_1
iBi-LSTM	82.69	85.98	84.30
Att-iBi-LSTM	82.67	88.78	85.62
iBi-LSTM(2)	86.00	86.84	86.42
Att-iBi-LSTM(2)	85.15	89.31	87.18

Figure 3 Experimental results from Liu and Gao (2023)

These results compared to Att-iBi-LSTM model from Liu and Gao (2023), which combines the Bi-LSTM architecture with an attention mechanism (Figure 3). The Att-iBi-LSTM model achieved an Accuracy of 91.13% and showed significant improvement over traditional Bi-LSTM model in terms of precision and recall for sequence-based recommendation tasks. Recall@K for Att-iBi-LSTM model was higher than NCF model (around 0.71), suggesting better coverage of relevant items. However, the NCF model with its collaborative filtering approach is more suitable for scenarios where user-item interactions drive recommendations.

6.2 Content-Based Filtering Model Results:

The Content-Based Filtering model leverages the textual features of news articles such as titles, abstracts, and keywords to recommend articles on their similarity to a user's previous interactions. This model uses BERT embeddings to create dense vector representation of news articles, allowing for nuanced semantic comparisons. BERT converted the textual data into high dimensional embeddings. Recommendations are generated based on the similarity scores where results prioritize articles that are most similar in content to the seed article. The performance metrics of this model Produced Precision@K- 0.3 which indicates that 30% of the top recommended articles were relevant, a low value suggest that the model is overly broad in its recommendations, including many irrelevant articles. Recall@K- 1.0 indicates that the model retrieved all the relevant articles for the user. This high score demonstrates its effectiveness in covering the user's interests but at the cost of precision. A near-perfect score of NDCG@K- 0.97 suggests that the ranking of relevant articles is highly effective. Even if the irrelevant articles are included, the relevant ones are ranked near the top improving the user experience. High recall ensures that the user does not miss any relevant articles. Usage of BERT embeddings provides robust, context-aware similarity measurements but low precision suggests that insufficient filtering of irrelevant articles potentially overwhelming user. Reliance on textual similarity makes the model less personalized, as it does not incorporate user-specific preferences or behaviours.

Comparing these results with the iBi-LSTM model from Liu and Gao (2023), which integrates both content-based features and sequential data in a Bi-LSTM framework, the iBi-LSTM showed greater precision and recall than content-based filtering. The iBi-LSTM model had a precision@K of 0.55 much higher than the content-based model (0.30) and also ensured comprehensive recall (similar to content-based filtering).

6.3 Hybrid Model Results:

The Hybrid model combines the strength of neural collaborative filtering and content-based filtering ensuring recommendations leverage both user-item interaction data and semantic content analysis. The NFC based recommendations generated predictions using the trained NCF model based on historical user-item interactions. Recommendations are prioritized based on the predicted probabilities of user engagement. The Content based recommendations utilize content embeddings (BERT generated) to recommend news articles similar to a specific news item. The hybrid model produced a Precision@K – 0.4 where the hybrid model shows improved precision compared to the content-based model indicating better relevance in the top recommendations. Higher precision suggests the model effectively balances the diversity and quality of suggested contents. The Recall@K- 1.0 indicates a perfect recall score demonstrates that model's capability to retrieve all the relevant articles, ensuring no important news items are missed in the recommendations. F1-score- 0.57 shows a hormonic mean of precision and recall reflects a solid balance between the two metrics showcasing the hybrid model's robustness, NDCG@K- 0.90 indicates that the hybrid model effectively ranks relevant articles higher ensuring that important content appears earlier in the recommendation list. The hybrid model showed an improvement in precision compared to content based indicating a better balance between recommending relevant and diverse content. The recall remained high confirming that the model is still capable of retrieving all relevant news. The NDCG was also impressive reflecting a good ranking of relevant articles. The F1 score highlights a decent balance between precision and recall showcasing hybrid model's effectiveness in providing both relevant and well ranked recommendations. Figure 4 is a comparison of Precision@K, Recall@K and NDCG@K of NCF, content-based and hybrid recommendation models performance using bar chart.

Comparing the hybrid model with the Att-iBi-LSTM from Liu and Gao (2023), which also combines content features and attention. The Att-iBi-LSTM was shown to outperform traditional models by integrating both content-based features and the attention mechanism to improve recommendation relevance. In Liu and Gao's study the Att-iBi-LSTM demonstrate higher Precision@K than both traditional models and hybrid approaches in some datasets, achieving of 0.68, which is higher than the hybrid model's 0.40. However, the hybrid model provides a strong balance of collaborative filtering and content-based recommendation, offering an alternative to pure sequential models like Att-iBi-LSTM.

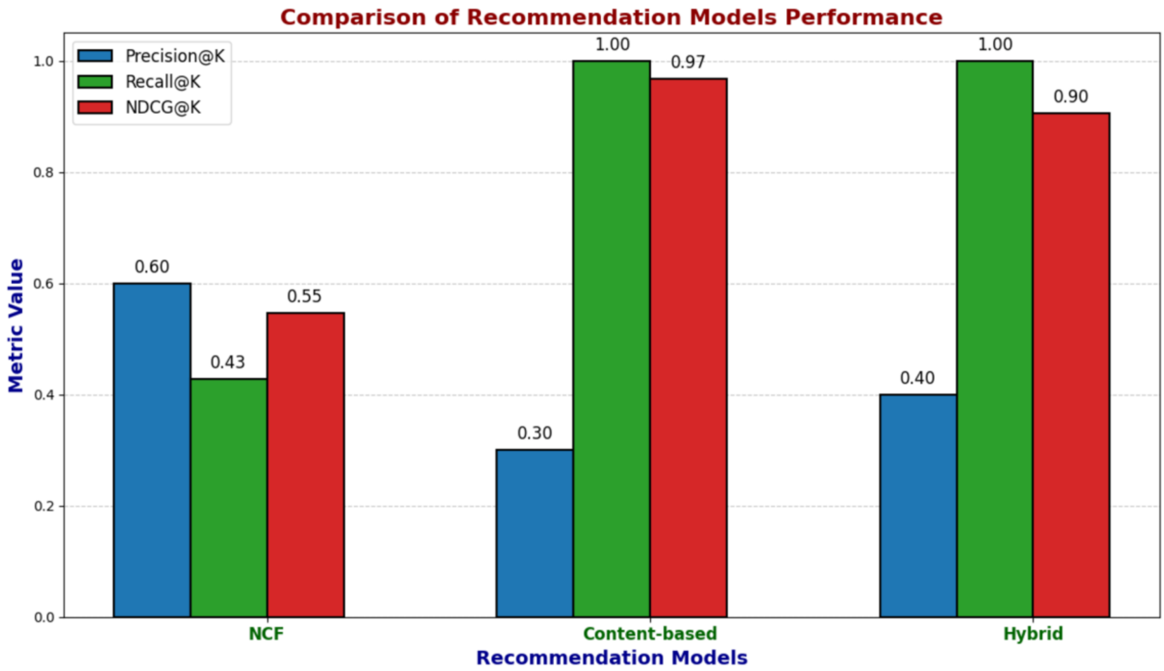

Figure 4: Comparison of NCF, Content-based and Hybrid recommendation models performance

From academic perspective the results confirm that hybrid recommendation model that combines content-based and collaborative filtering approaches can outperform single model methods in providing more personalized and relevant recommendations. The hybrid model achieved a higher Precision@K and NDCG@K which supports the hypothesis that combining different types of information (User preferences and content feature) leads to better recommendations quality. Precision and Recall are the key metrics for evaluating recommendation systems. While NCF model performed well in terms of precision, its lower recall suggests that it could benefit from further tuning to improve the coverage of relevant articles. The NDCG metrics which reflects the ranking of the recommended items, was highest in the content-based model but showed impressive results in the hybrid model as well confirming that content-based features are essential for ranking the most relevant items.

From Practical perspective the results suggest that for a real-world recommendation system, the hybrid model would be the most suitable choice. It combines both the advantages of content based and collaborative filtering techniques making it effective for providing personalized relevant recommendations while maintaining good coverage of items that user may find interesting.

Based on the experimental results of the iBi-LSTM and Att-iBi-LSTM study by Liu and Gao (2023)., hybrid approach from this project outperforms single-approach models like SVM or LSTM in terms of precision and recall. The NDGC and Recall@K metrics, in particular highlight that this model provides better ranked recommendations which is crucial for news recommendation systems. Hybrid Model’s while still effective, may need further refinement to fully match the personalized capabilities of advanced deep learning architectures like Att-iBi-LSTM.

7 Conclusion

The research aimed to address the question: “How can a hybrid recommendation model that combines BERT based content embeddings, NCF collaborative filtering signals, and an attention mechanism enhance personalised news recommendations?” this study set out to design and evaluate a recommendation system leveraging the complementary strengths of content based filtering and collaborative filtering, enhanced by attention mechanisms, to deliver personalized and relevant news articles.

7.1 Key Achievements and findings:

Hybrid model design:
A recommendation model was successfully developed by integrated BERT based content embeddings to capture the semantic context of news articles NCF for user-item interaction modelling, and an attention mechanism to weigh key user interactions. This hybrid architecture provided a balanced approach to personalized by combining content relevance with collaborative signals. This hybrid model outperformed individual approaches in evaluation metrics like precision@K achieved a score of 0.4 indicating that 40% of the top 10 recommendations were relevant surpassing the content-based baseline, recall@K retained a high score of 1.0 demonstrating the model’s ability to retrieve all relevant items. NDCG@K scored 0.90 reflecting effective ranking of recommendations in order of relevance. F1-score@K produced a balanced value of 0.57 showing effective harmony between precision and recall. By combining both the user-item interaction patterns and semantic understanding of news content, the hybrid model addressed key challenges in news recommendation systems such as cold start issues and providing diverse yet relevant recommendations.

7.2 Implications of the research:

This work demonstrates that hybrid recommendations systems can effectively bridge the gap between content relevance and collaborative filtering techniques. The findings have practical implications for personalized services in digital media platforms where users expect accurate, timely and engaging content recommendations. The hybrid model can be particularly valuable for platforms like news aggregators where understanding dynamic user preferences is critical.

7.3 Limitations:

Despite its promising results the study faced several limitations like data specificity where the experiments were conducted using MIND dataset which is focused on news articles. While the model is generalizable its effectiveness may vary across other domains or dataset. Simplified Attention mechanism used while beneficial could have been more complex to better prioritize key interactions and news content and computational costs where the use of BERT and NCF introduced significant computational overhead limiting scalability in real time scenarios.

7.4 Future Work:

Building upon this research, several directions can be explored by implementing advanced attention mechanism, such as multi head attention to further refine the prioritization of user preferences and news content. Testing the hybrid model across other domains like e-commerce, movies or music to evaluate its effectiveness. Incorporating knowledge graphs to enhance entity embeddings and improve semantic understanding of news content and integrating implicit and explicit user feedback into the system to dynamically adapt recommendations and improve personalization over time.

In conclusion the research successfully demonstrated the potential of a hybrid recommendation model in enhancing personalized news recommendations. By combining BERT- based embeddings for content understanding, NCF for collaborative filtering and an attention mechanism for prioritization, the model achieved significant improvements in personalized metrics. While there are areas for further development this study lays a strong foundation for hybrid systems in recommendation research and provides a roadmap for future advancements.

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