# CHAPTER TWO

### INTRODUCTION

The purpose of this literature review is to critically evaluate the existing research on deep learning models for personalized book recommendations. The aim is to identify the strengths and limitations of current approaches, highlight the research gaps and challenges and provide a basis for the development of a novel deep learning model for personalized book recommendation.

### BACKGROUND

Book recommendation systems are software applications that suggest books to users based on their interests and preferences. The goal of these systems is to help users discover books that they might be interested in reading but might not otherwise have discovered on their own.

There are two main types of book recommendation systems: content-based and collaborative filtering. Content-based systems use information about the content of the books, such as genre, author, and topic, to make recommendations. Collaborative filtering systems, on the other hand, use information about the user's past behavior and the behavior of other users to make recommendations.

In recent years, deep learning models have become increasingly popular for book recommendations. These models use artificial neural networks and other machine learning techniques to process large amounts of data and make recommendations based on patterns and trends in the data. Deep learning models can incorporate a wide range of data, including user behavior, book metadata, and social network information, to make highly personalized recommendations.

However, there are several challenges associated with developing effective book recommendation systems. These include the cold start problem, which occurs when there is not enough user data to make accurate recommendations for new users, and the problem of data sparsity, which occurs when there is not enough data on certain books or users to make accurate recommendations. Additionally, privacy concerns related to user data collection and usage are an important issue that must be addressed when developing book recommendation systems.

This brief overview of book recommendation systems sets the stage for the subsequent sections of the literature review, which will dive deeper into the different types of recommendation systems and the challenges associated with developing effective deep learning models for personalized book recommendations.

## LITERATURE REVIEW

### 1.1 Personalized Recommendation system

Personalized recommendation system is a computer-based system that offers individualized recommendations to users based on their previous behavior or history. According to Dina F. et al. (2018), a recommender system in the context of education provides intelligent recommendations to students about study materials, courses, and related information based on their prior decisions. To provide such recommendations, the system employs a statistical model that is trained using a learning algorithm based on input from previous learning participants.

In a personalized recommendation system, users and items are the two main objects that play a crucial role. Users provide their interests about items, and this information is accumulated as input data in a utility matrix. The utility matrix represents the order of preference for particular items by the user in the combination of customer-item value. There are two classifications of recommender systems: user-based and item-based. In a user-based system, the user's interests, dislikes, and ratings are used to recommend unrated items. In contrast, an item-based system utilizes the relationship among items to generate recommendations from users (M.P. Geetha, D. Karthika R., 2019).

Recommender systems play a vital role in both academia and industries. Many companies use RS in their sales promotion, utilizing various platforms. For instance, the majority of the most-watched movies on YouTube and other online video databases come from the RS (Aminu D. & Naomie S. 2019).

All authors agree that a personalized recommendation system is a system created with the major aim of recommending useful information or items to users based on past learned historical records relating to the individual’s tastes and preferences.

### 1.2 Traditional Machine Learning Model

The emergence of traditional recommendation system can be traced back to the extensive research in cognitive science, approximation theory, information retrieval, forecasting theories, and also to management science related and to consumer choice modeling in marketing i.e., E-commerce. The recommender systems emerged as an autonomous research domain in the mid-1990s. This is the period where researchers started to focus on the recommendation problems that rely solely on ratings structure. The recommendation problem is reduced to the problem of recommender system to be estimating ratings for the items that have not been seen or rated by the user. Intuitively, this prediction or estimation is usually based on the user’s previous rated items. In this sense, if the estimate ratings for the yet unrated items can be obtain, then the item(s) with the highest estimated rating(s) can be predicted to the user (Gediminas, Alexander et al., 2005).

In the context of book recommendation system, the traditional recommender systems can help personalize and suggests books to users based on their preferences, past reading history, and other relevant factors (Khalid & Jamshed, 2020).

For example, in a study conducted in 2021, traditional machine learning models were used to develop a book recommendation system based on users' reading preferences (Cheng et al., 2021). The study utilized data from Goodreads, a popular online book database, to train the models. The results showed that the developed models could accurately recommend books to users based on their reading preferences. Another study conducted in 2020 used traditional machine learning models to develop a book recommendation system for children (Barros et al., 2020). The study utilized data on children's reading habits and preferences to train the models. The results showed that the developed models could recommend books that were both age-appropriate and of interest to the children. In both studies, traditional machine learning models were used to develop book recommendation systems that could accurately predict users' book preferences. These systems have the potential to improve the reading experience for users by providing personalized recommendations tailored to their interests.

In traditional machine learning-based book recommendation systems, the algorithms are trained on large datasets of book ratings, reviews, and other relevant data. The models use this data to recognize patterns and make predictions on which books a user is likely to enjoy.

The algorithm for estimating the not-yet-rated items in the traditional recommendation context is classified into three, namely: collaborative filtering, content base and hybrid approach (Kunal, Akshaykumar et al., 2017).

### 1.2.1 Type of Traditional recommendation system

There are three different types of traditional recommendation systems:

1. Collaborative filtering
2. Content base
3. Hybrid approach

##### **1.2.1.1 Collaborative Filtering (CF)**

The term collaborative filtering was coined in 1992 by Goldberg et al., who proposed that information filtering becomes more effective when human group relational preferences or involvements are consider while recommending items to users (Kunal, Akshaykumar, et al., 2017). This method of recommendation tries to predict the utility of items for a particular user based on the items previously rated by other similar users (Gediminas, Alexanda, et al., 2005). According to Kunal et al. (2017), believe collaborative filtering to be a method of recommendation system in which recommendations are generated to various users by actively comparing the preferences of one active user with another who have qualified products similarly with the user in the past. CF are based on the idea that people who agree with the evaluation of items in the past are likely to agree again in future. Collaborative filtering method are grouped into two general classes: neighborhood based and model-based (Gediminas, Alexanda, et al., 2005; Kunal, Akshaykumar, et al., 2017).

*A. Neighborhood Based Method*

The neighborhood-based method of collaborative filtering, also known as memory-based or heuristic-based CF, leverages the user-item ratings stored in memory to make predictions about the preferences for new items. This can be accomplished through two approaches: user-based and item-based recommendation (Qian, Jie, et al., 2020).

In the user-based approach, the interest of a user (referred to as "u") in an item (referred to as "i") is determined by considering the ratings given to that item by other users who exhibit similar rating patterns. These users are known as "neighbors". By examining the ratings of these neighbors, the system can estimate the likelihood of user u being interested in item i (Dhanashri, Nandani, et al., 2020).

On the other hand, the item-based approach involves predicting the rating that user u would assign to item i based on the ratings that user u has given to items similar to i. In this approach, the similarity between two items is calculated by examining the ratings provided by other users of the system. By analyzing these ratings, the system can identify items that are similar in terms of user preference and use this information to make predictions about user u's rating for item i (Bushra, Imran, et al., 2019).

Overall, the neighborhood-based method of collaborative filtering utilizes the existing user-item ratings to determine recommendations for new items. The user-based approach focuses on finding users with similar rating patterns, while the item-based approach concentrates on identifying similar items based on user ratings. By employing these methods, the system can provide personalized recommendations that align with user preferences.

Kunal et al. (2017) classified the main advantages of neighborhood-based methods as follow:

* Simplicity: Neighborhood-based methods are relatively straightforward to implement, making them accessible and easy to work with.
* Efficiency: This method does not require expensive training phases that need to be regularly performed in large commercial applications. This saves computational resources and time.
* Justifiability: Neighborhood-based methods provide concise yet comprehensive explanations for their predictions. This makes it easier for users to understand why certain recommendations are made.
* Stability: Despite the continuous addition of items, users, and ratings typically encountered in major e-commerce applications, neighborhood-based methods remain relatively unaffected. They maintain stability in their recommendations even as the system evolves over time.

*B. Model-Based Recommendation Methods*

The model-based recommendation method differs from neighborhood-based systems in that it doesn't directly use stored ratings for prediction. Instead, it utilizes these ratings to acquire knowledge and build a predictive model. In model-based approaches, the aim is to replicate and model the interactions between users and items, incorporating factors that represent the hidden characteristics of both users and items within the system. These factors can include user preferences and item categories, among others.

To implement a model-based system, the available data (usually in the form of a training dataset) is used to train the predictive model. The model is trained to understand the patterns and relationships between users, items, and their hidden characteristics. Once the model is trained, it can be applied to predict ratings for new items based on user behavior and item attributes.

Numerous model-based approaches exist for the task of item recommendation, each employing specific techniques. These techniques include Bayesian Clustering, which utilizes probabilistic clustering algorithms; Latent Semantic Analysis, which applies matrix factorization techniques to uncover latent factors in user-item interactions; Support Vector Machines, which employ machine learning algorithms for classification and regression tasks; and Singular Value Decomposition, which decomposes the user-item rating matrix into lower-dimensional representations.

These model-based approaches offer a more sophisticated and comprehensive way to make recommendations by capturing underlying patterns and relationships within the data. They leverage machine learning and statistical techniques to create predictive models that can effectively estimate user ratings for new items, enhancing the recommendation process.

### 1.2 Deep Learning Model

### 1.3 Deep Learning Model vs Traditional Recommendation system