BAB I

In the ever-evolving digital era, recommender system technology has become inevitable. Its role is crucial in helping users manage the vast amount of information on the internet while providing recommendation tailored to their individual preferences. One commonly encountered case is e-commerce, which has become the primary platform for consumers to meet their daily needs, including purchasing groceries. However, with the increasing variety of product choices and diverse user preferences, service providers face challenges in delivering a shopping experience that is both personal and relevant. Personalized recommender systems have emerged as an effective solution to help consumers find products that match their preferences while simultaneously enhancing customer loyalty and increasing service provider revenue.

One of the popular approaches in developing recom- mender systems is collaborative filtering, which leverages user interaction patterns and preferences to provide recom- mendations that enhance user experience [13]. With tech- nological advancements, matrix factorization-based collab- orative filtering methods, such as Singular Value Decom- position (SVD), have become increasingly popular. Zheng et al. [11] discuss that SVD decomposes the user-item interaction matrix into latent representations, which helps capture hidden relationships in the data. However, this method has limitations as it only utilizes explicit data and often overlooks implicit data, which plays a significant role. To address these limitations, SVD++ was develop by incorporating implicit interaction patterns between users and products. SVD++ can improve prediction accuracy [5], including in the e-commerce domain. Niu et al. [1] highlight two main limitations of SVD++: (i) it only utilizes im- plicit feedback from the user side, while implicit feedback from the item side is not leveraged; (ii) in SVD++, items interacted with are given equal weight when combining implicit feedback. Jain et al. [12] note that Collaborative Filtering (CF) is an effective recommendation method for providing personalized suggestions to users but often fails to account for changes in user preferences over time, which can be addressed by integrating temporal aspects into recommender systems. Incorporating temporal factors into recommendation models is critical in improving rec- ommendation personalization, especially for e-commerce.

In previous studies, various approaches have been un- dertaken to develop recommender systems, including col- laborative filtering methods based on matrix factorization such as SVD and SVD++. Previous studies revealed that SVD++ has advantages over SVD in modeling implicit feedback and improving recommendation accuracy [24] [26]. However, most of these studies have not considered the temporal context, particularly in the domain of grocery e-commerce, which exhibits dynamic consumption patterns. Zhang et al. [25] introduced the TimeSVD++EXP method, which integrates time-based exponential correction to capture changes in user preferences in movie recommen- dations, demonstrating improvements in evaluation metrics, underscoring the importance of integrating time factors. Therefore, we propose the development of a time-based collaborative filtering method, i. e., TimeSVD++, designed to account for time information in a more dynamic and holistic manner. Unlike standard SVD++, this method leverages implicit data combined with time analysis by as- signing greater weight to times frequently used by specific users, identified as key moments based on user behavior patterns. This study not only reinforces previous findings on the importance of the time dimension but also extends the scope of time integration by capturing more complex and contextual temporal patterns, particularly in the grocery e-commerce domain. This approach aims to deliver a more personalized and efficient shopping experience for users. The grocery e-commerce domain is chosen due to its high relevance in illustrating consumption patterns heavily influenced by temporal factors, such as shopping habits on weekdays, weekends, mornings, afternoons, or evenings. By integrating time information into the recommendation method, this system is expected to enhance user satisfaction and the effectiveness of grocery e-commerce services.

This paper consists of five main sections. Chapter 1 discusses the background, motivation, and objectives of the research. Chapter 2 reviews relevant previous studies. Chapter 3 explains the research stages, including the use of the dataset, the recommendation process, and the imple- mentation of the TimeSVD++ method. Chapter 4 contains the model evaluation and a performance comparison anal- ysis between the models with and without time. Finally, Chapter 5 concludes the research findings and provides directions for future development.