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Non-IID Recommender Systems: A Review and Framework of Recommendation Paradigm Shifting

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A B S T R A C T

While recommendation plays an increasingly critical role in our living, study, work, and entertainment, the recommendations we receive are often for irrelevant, duplicate, or uninteresting products and services. A critical reason for such bad recommendations lies in the intrinsic assumption that recommended users and items are independent and identically distributed (IID) in existing theories and systems. Another phenomenon is that, while tremendous efforts have been made to model specific aspects of users or items, the overall user and item characteristics and their non-IIDness have been overlooked. In this paper, the non-IID nature and characteristics of recommendation are discussed, followed by the non-IID theoretical framework in order to build a deep and comprehensive understanding of the intrinsic nature of recommendation problems, from the perspective of both couplings and heterogeneity. This non-IID recommendation research triggers the paradigm shift from IID to non-IID recommendation research and can hopefully deliver informed, relevant, personalized, and actionable recommendations. It creates exciting new directions and fundamental solutions to address various complexities including cold-start, sparse data-based, cross-domain, group-based, and shilling attack-related issues.

1. Introduction

Recommendation [1,2] is a major application of big data [3,4]. It plays an increasingly important role in both core business and new economy, particularly when it involves social media, mobile services, online business, and study and living. In recent years, recommendation research has attracted significant attention in many communities, including recommender systems, information retrieval, social media, social networks, machine learning, data mining, and data engineering.

A quality recommendation service should refer the most relevant products (services or other items) to the right people at the right time. Intensive efforts have been made, especially in the recommendation and information-retrieval communities, to improve recommendation quality, by considering specific factors such as social relationships, friendship, user comments on purchased products, grouping similar behaviors or categories of products, and recommending products from another domain.

In most cases, however, we have seen irrelevant or even brand-damaging recommendations of products or services to us through channels including news portals, online shopping websites, and mobile applications. For example, a famous search engine website placed an advertisement suggesting a visit to Greek beaches alongside a news article about civil protest taking place in Greece. Another website recommended different kinds of fruit to a user who showed interest in kiwis (a New Zealand bird), assuming that the user's interest was in kiwi fruit. Online bookselling websites often list books that either duplicate those we have already purchased or are totally irrelevant.

Some critical questions facing the recommendation commu-

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nity include: Why are we recommended irrelevant or duplicated products and services? and more critically, What makes next-generation recommendation? To answer these questions, even more fundamental problems need to be studied, including:

- What foundational aspects have been missing in existing recommendation theories and systems that result in poor recommendations?
- How can informed, relevant, personalized, and actionable recommendations be made?
- How can recommendation quality be improved so that only those products that are relevant to individual or group user interests, preferences, and circumstances are pushed forward?
- What are new recommendation methodologies are essential for a unified theoretical framework that can capture the intrinsic characteristics and complexities in recommendation?
- What is the paradigm shift of recommendation research that fundamentally enables the next-generation research?
- What forms the foundation of next-generation recommendation?
- What are the new directions for the next generation of recommendation theories and systems?
- What new recommendation theoretical foundation can address typical challenges including cold-start, sparsity, cross-domain, group recommendation, and shilling attack?

While there are many aspects to be explored in order to address the above foundational problems, one particular perspective that is of interest in this paper concerns the in-depth understanding of recommended users and items, and the tight connection between the ratings given by a user to an item and the characteristics of users and items. This involves an in-depth understanding of the intrinsic characteristics and complexities in recommendation, and the nature of recommendation; that is, the heterogeneity and couplings (namely non-IIDness [5,6]) of ratings, user properties, and item properties, and the heterogeneity and couplings among these three aspects.

In existing recommendation research, various efforts have been made on high-level aspects such as user ratings on items, user social relationships, and comments on items. Such efforts may be generally categorized into the following aspects: ① estimating future ratings based on existing ratings, ② incorporating user comments on items into modeling, ③ incorporating user friendliness into modeling, ④ modeling group preferences or behaviors, and ⑤ learning the user preference transfer across domains. User behaviors of viewing or commenting on items are also modeled in Refs. [7,8]. More recently, coupling relationships between items and user groups have been modeled for recommendation [9–11], bringing low-level driving forces into rating dynamics estimation.

However, state-of-the-art recommendation research [2] has been built on the assumption that users, products, and ratings are independent and identically distributed (IID), resulting in IID models and methods [5]. No work has considered very low-level non-IID information about specific users and items. In this way, the fundamental driving forces of ratings are simplified or overlooked, which this author believes is a critical reason for the poor performance of existing recommender systems and services. For example, matrix factorization (MF) is a generic mathematical tool widely used in recommendation modeling. However, it will generate similar outcomes for houses and cars if the low-level properties of houses and cars are not involved and if houses and cars are treated as IID. This creates a significant gap between general high-level models and the specific low-level information associated with recommended users and items.

This paper focuses on discussing the driving role of such information in capturing the nature of recommendation and improving recommendation quality. By extending the brief discussion in Ref. [12] about non-IID recommendation theories and systems, a systematic framework and an in-depth understanding of recommendation nature are provided. This paper discusses the issues in existing research, and examines the need for, and concepts of, next-generation recommendation theories and techniques to address non-IIDness in recommendation. A general non-IID learning framework is proposed that captures both high-level ratings dynamics and low-level specific information on users and items and their non-IID nature.

Non-IIDness involves coupling relationships and heterogeneity in recommendation. The couplings involve subjective and objective interactions as well as explicit and implicit interactions within and between users, within and between items, and between users and items. Heterogeneity spreads from users to items, as well as to their properties. Non-IID recommendation research specifically considers the following aspects: ① low-level explicit properties of non-IID users and items involved in a recommender system; ② heterogeneity between users and between items; ③ hierarchical coupling relationships [6] within and between users and items, and between users and items; and ④ latent interactions within and between users and items, and between users and items.

Such a non-IID recommendation perspective opens paradigm-shifting opportunities and new directions for next-generation foundational research and quality recommendation. In fact, learning non-IIDness [5,6] in big data is a foundational theoretical and practical challenge in data science and big data analytics [3,13–15], which has not been paid much attention in relevant communities including computing, informatics, and statistics, because existing analytics and learning theories and systems have been mainly built on the IID assumption. The discussions about non-IID recommendation theories and systems in this work will hopefully inspire fundamental research and promising outcomes in other analytical, learning, and information-processing areas.

This paper is organized as follows. First, Section 2 discusses the intrinsic nature of recommendation problems. Section 3 presents the concept of recommendation non-IIDness. Section 4 summarizes the main issues, with a particular focus on the IID assumption that is associated with existing recommender systems and theories. Section 5 outlines the paradigm shift of recommendation research in terms of the features and generations of recommendation research. Section 6 introduces a non-IID recommendation framework and the non-IID recommendation statement. Section 7 summarizes some preliminary case studies of non-IID recommendation methods. Prospects regarding non-IID recommendation are outlined in Section 8, followed by conclusions in Section 9.

2. Nature of recommendation

This paper combines the multiple sources of information related to recommendation in terms of the example shown in Fig. 1. A four-table view of recommendation is built, which consists of the following four spaces of information:

- The rating information in Table A in Fig. 1. This consists of all ratings by users on items, and embeds user rating behaviors and preferences. Table A reflects the subjective information and outcomes in recommendation.
- The user information in Table B. This reflects user characteristics, properties, and relationships that drive their rating behaviors and preferences. Table B consists of objective factors of users.
- The item information in Table C. This demonstrates item