Non-compensate Recommendation Models

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***Abstract*—The study of consumer psychology reveals two categories of procedures used by consumers to make consumption related choices: compensatory rules and non-compensatory rules. Existing models assume the consumers follow the compensatory rules, which are to make decisions based on a weighted or summated score over different aspects. In this paper, we present a novel model which adopts non-compensatory decision rules. An item is selected because (1) it is superior on the most important aspect, and (2) its performance is beyond the minimally acceptable level on other aspects. Furthermore, we incorporate other psychological concepts such as evaluation process and ordinal utility to predict consumption in activity sessions. We experimentally demonstrate that this model outperforms state-of-the-art methods.**

***Index Terms*—compensatory decision rules, non-compensatory decision rules, factor models**

I. Introduction

Recommender **S**ystem (RS) has received a lot of research attention. In the fruitful literature of RS, latent factor models are the most ubiquitous and successful because of their dominanting performance. Latent factor models represent users and items as vectors of factors with the same dimensions [**?**], [**?**]. Inner products of the latent factor vectors of users and items are used to reconstruct the observations, which could be either point-wise values (i.e. the numerical ratings users give to items []) or pair-wise rankings (i.e. the order between a pair of user feedback []).

Intuitively, a user's factors in latent factor models encode the user's "preferences" on some hidden "aspects", while an item's factors convey information about the item's "property" on the same aspects. The inner product describes the summated score over all aspects that a user assigns to an item. From the perspective of users, the scoring of an item is based on compensatory rules, i.e. the shortcomings of an item are balanced out by its strongpoints. For example, suppose consumers make decisions based on three hidden aspects: "price","quality" and "others". As illustrated in Fig. 1, a user with preference vector $u = [0.5, 0.4, 0.1]$ is comparing two items $v_1 = [0.7, 0.1, 0.2]$ and $v_2 = [0.6, 0.35, 0.05]$. If the user adopts compensatory decision rules, he will prefer v_2 because the summated score of v_2 over all aspects is higher (i.e. the red area is larger than the blue area).

Existing latent factor models in RS community are implementations of the compensatory decision rules. However, in the field of psychological science, ample evidence [**?**] exist to support that, consumers adopt non-compensatory rules more often to make consumption decisions. Non-compensatory rules do not allow a good performance on one aspect of an item to make up for poor performances on other aspects. In the study of consumer psychology, non-compensatory rules include *lexicographic, conjunction and disjunction* rules. Under lexicographic rules, items are compared on the most important aspect. For example, in Fig. 1, if the user adopts lexicographic rules, v_1 is the winner because v_1 is superior on the most important aspect "price". Under conjunction and disjunction rules, the consumer imposes requirements for minimally acceptable performance on each aspect separately. For example, if the user in Fig. 1 adopts conjunction or disjunction rules, and the minimum requirement is 0.08 on every aspect, then v_1 will be chosen.

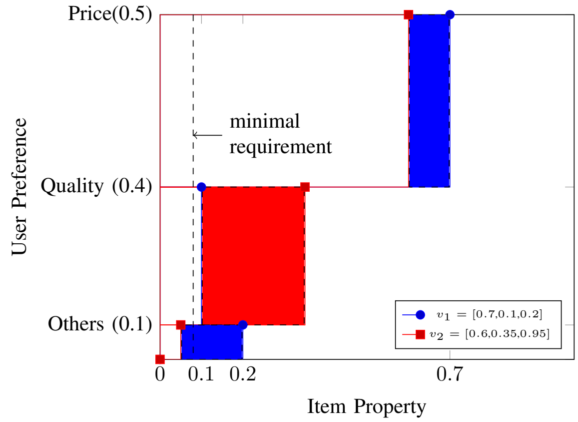

Fig. 1. Difference between compensatory rules and non-compensatory rules: compensatory rules prefer v_2, while non-compensatory rules prefer v_1.

To the best of our knowledge, there is no RS model that is based on non-compensatory decision making rules. In this work, we seek to answer the following three research questions. (1) Are non-compensatory rules more suitable to model user behavior in recommender systems? (2) Do users follow the same non-compensatory rules to give different feedback, i.e. explicit feedback and implicit feedback? (3) Can we handle massive recommender systems?

To address the first problem, we study the generation of pair-wise observations in a recommender system. We are inspired by psychological discoveries that conjunction and disjunction rules are found to be often used in conjunction with lexicographic rules. Therfore, we propose a **C**omplete **N**on-**C**ompensatory (CNC) model which uses both lexicographic and conjunction rules. We assume that an item is preferred in a pair of items because it is significantly better on the user's favorite aspect, and it is satisfactory on other aspects.

The second problem is motivated by the heterogeneous types of user feedback available in recommender systems. We consider three types of user feedback, explicit feedback which contains user-item ratings, graded sessional feedback which contains user actions in a session that we can rank (e.g. a purchase ranks higher than a click) and binary implicit feedback (e.g. click v.s. non-click). Explicit feedback and graded sessional feedback are clear indicators of user preference, while binary implicit feedback is noisy (i.e. a clicked item is not neccessarily preferred than a non-clicked item). The CNC model is based on a complex evaluation of all aspects, and thus could be too "strict" for noisy binary implicit feedback. Therefore, we present a **S**implified **N**on-**C**ompensatory (SNC) model, which is based purely on lexicographic rules and only considers the user's favorite aspect.

The third problem is related to the scalability of the proposed models. To deal with large-scale mordern recommender systems, we derive stochastic EM inference algorithms for the proposed models. Stochastic EM algorithms are more effcient than EM algorithms. Futhermore, inspired by the SECA framework [], we present to parrallize the stochastic EM inference.

Our contributions are three folds. (1) We propose a novel recommendation model (CNC model) which is based on a set of combined non-compensatory rules. Conprehensive experiments demonstrate that, CNC significantly outperforms state-of-the-art latent factor models on explicit and graded sessional feedback. (2) We propose a novel recommendation model (SNC) model which is based on simple non-compensatory rules. Comprehensive experiments reveal that, for binary implicit feedback, SNC model significantly outperforms state-of-the-art latent factor models and CNC model. (3) We present highly parrallel and efficient inference algorithms for both models.

This paper is structured as follows. We briefly introduce related work in Sec. II. The main contributions of this paper are described in Sec. III to Sec. V. The CNC model for explicit and graded sessional feedback is presented in Sec. refsec:model1. The SNC model for binary implicit feedback is presented in Sec. IV. The highly parrallel algorithm is presented in Sec. V. We analyze experimental results on real recommendation data sets in Sec. VI. Finally, we conclude our work and give future directions in Sec. VII.

II. Related Work

III. Complete Non-compensate Rules for Explicit Feedback

An item is chosen if it scores sufficiently higher than other items.

IV. Simplified Non-compensate Rules for Implicit Feedback

V. Highly Parrallel Inference

VI. Experiment

A. Experimental Setup

B. Comparative Performance on Explicit Feedback

C. Comparative Performance on

VII. Conclusion

References

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