

# Recommender Systems: The Textbook



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# Recommender Systems

The Textbook

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*To my wife Lata, my daughter Sayani,  
and my late parents Dr. Prem Sarup and Mrs. Pushplata Aggarwal.*



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# Preface

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*“Nature shows us only the tail of the lion. But I do not doubt that the lion belongs to it even though he cannot at once reveal himself because of his enormous size.”* – Albert Einstein

The topic of recommender systems gained increasing importance in the nineties, as the Web became an important medium for business and e-commerce transactions. It was recognized early on that the Web provided unprecedented opportunities for personalization, which were not available in other channels. In particular, the Web provided ease in data collection and a user interface that could be employed to recommend items in a non-intrusive way.

Recommender systems have grown significantly in terms of public awareness since then. An evidence of this fact is that many conferences and workshops are exclusively devoted to this topic. The *ACM Conference on Recommender Systems* is particularly notable because it regularly contributes many of the cutting-edge results in this topic. The topic of recommender systems is very diverse because it enables the ability to use various types of user-preference and user-requirement data to make recommendations. The most well-known methods in recommender systems include collaborative filtering methods, content-based methods, and knowledge-based methods. These three methods form the fundamental pillars of research in recommender systems. In recent years, specialized methods have been designed for various data domains and contexts, such as time, location and social information. Numerous advancements have been proposed for specialized scenarios, and the methods have been adapted to various application domains, such as query log mining, news recommendations, and computational advertising. The organization of the book reflects these important topics. The chapters of this book can be organized into three categories:

1. *Algorithms and evaluation*: These chapters discuss the fundamental algorithms in recommender systems, including collaborative filtering methods (Chapters 2 and 4), content-based methods (Chapter 4), and knowledge-based methods (Chapter 5). Techniques for hybridizing these methods are discussed in Chapter 6. The evaluation of recommender systems is discussed in Chapter 7.
2. *Recommendations in specific domains and contexts*: The context of a recommender system plays a critical role in providing effective recommendations. For example, a

user looking for a restaurant would want to use their location as additional *context*. The context of a recommendation can be viewed as important side information that affects the recommendation goals. Different types of domains such as temporal data, spatial data, and social data, provide different types of contexts. These methods are discussed in Chapters 8, 9, 10, and 11. Chapter 11 also discusses the issue of using social information to increase the trustworthiness of the recommendation process. Recent topics such as factorization machines and trustworthy recommender systems are also covered in these chapters.

3. *Advanced topics and applications*: In Chapter 12, we discuss various robustness aspects of recommender systems, such as shilling systems, attack models, and their defenses. In addition, recent topics, such as learning to rank, multi-armed bandits, group recommender systems, multi-criteria systems, and active learning systems, are discussed in Chapter 13. An important goal of this chapter is to introduce the reader to the basic ideas and principles underlying recent developments. Although it is impossible to discuss all the recent developments in detail in a single book, it is hoped that the material in the final chapter will play the role of “breaking the ice” for the reader in terms of advanced topics. This chapter also investigates some application settings in which recommendation technology is used, such as news recommendations, query recommendations, and computational advertising. The application section provides an idea of how the methods introduced in earlier chapters apply to these different domains.

Although this book is primarily written as a textbook, it is recognized that a large portion of the audience will comprise industrial practitioners and researchers. Therefore, we have taken pains to write the book in such a way that it is also useful from an applied and reference point of view. Numerous examples and exercises have been provided to enable its use as a textbook. As most courses on recommender systems will teach only the fundamental topics, the chapters on fundamental topics and algorithms are written with a particular emphasis on classroom teaching. On the other hand, advanced industrial practitioners might find the chapters on context-sensitive recommendation useful, because many real-life applications today arise in the domains where a significant amount of contextual side-information is available. The application portion of Chapter 13 is particularly written for industrial practitioners, although instructors might find it useful towards the end of a recommender course.

We conclude with a brief introduction to the notations used in this book. This book consistently uses an  $m \times n$  ratings matrix denoted by  $R$ , where  $m$  is the number of users and  $n$  is the number of items. The matrix  $R$  is typically incomplete because only a subset of entries are observed. The  $(i, j)$ th entry of  $R$  indicates the rating of user  $i$  for item  $j$ , and it is denoted by  $r_{ij}$  when it is actually observed. When the entry  $(i, j)$  is *predicted* by a recommender algorithm (rather than being specified by a user), it is denoted by  $\hat{r}_{ij}$ , with a “hat” symbol (i.e., a circumflex) denoting that it is a predicted value. Vectors are denoted by an “overline,” as in  $\overline{X}$  or  $\overline{y}$ .

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## Author Biography

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