Complex Item Set Recommendation

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ABSTRACT

In this tutorial, we aim to shed light on the task of recommending a set of multiple items at once. In this scenario, historical interaction data between users and items could also be in the form of a sequence of interactions with sets of items. Complex sets of items being recommended together occur in different and diverse domains, such as grocery shopping with so-called baskets and fashion set recommendation with a focus on outfits rather than individual clothing items. We describe the current landscape of research and expose our participants to real-world examples of item set recommendation. We further provide our audience with hands-on experience via a notebook session. Finally, we describe open challenges and call for further research in the area, which we hope will inspire both early stage and more experienced researchers.

CCS CONCEPTS

• **Information systems** → **Recommender systems**;

KEYWORDS

Set recommendation, Basket recommendation

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1 MOTIVATION

Recommender systems have provided a central discovery channel for users in different platforms, parallel to search. Depending on the domain, type of input and context available, recommender systems have been designed for different scenarios. As an example, session-based recommendation has received extensive attention in the past years [18, 21, 31, 32]. Still, most of the recommendation endeavors focus on either a single item being recommended to a user, or a disjoint collection of those single items [16, 18, 26, 27, 30, 36].

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Item set recommendation. In this tutorial, we aim to shed light on the task of recommending a set of multiple items at once. In this scenario, historical interaction data between users and items could also be in the form of a sequence of interactions with sets of items. Complex sets of items being recommended together occur in different and diverse domains, such as grocery shopping with so-called baskets [19], fashion set recommendation with a focus on outfits rather than individual clothing items [22], travel packages [6], in-game item set recommendation [9], recommending reading lists [15], and music playlist creation [8].

Item set recommendation differs from widely studied sequential and top-n recommendation. When the input and output are in forms of sets of items, relations among items such as being complementary becomes importance. Moreover, modeling sets of items poses additional challenges, as there can be complex correlations and information within a set and among different sets of items. Considering budget constraints is another important aspect in recommending item sets; such constraints are typical and could be in form of money, volume, or duration limits.

Evaluating recommended sets of items. In addition to representation learning and modeling challenges for item sets, evaluation of systems recommending sets of items needs special attention. Beyond being accurate in terms of relevance, in many domains such as music recommendation, it is important that the items in a recommended set have a common characteristic, such as mood or music genre. When curating sets consisting of previously seen and novel items, having the right amount for each category becomes important.

Going beyond recommending a single item has gained attention in the research community. As an example, in a recent resource paper, Sun et al. [29] introduce three new bundle datasets to facilitate research on intent-aware product bundling. Extensive experiments are performed across different tasks such as bundle detection, showing both research challenges and opportunities for product bundling in real e-commerce platforms. In another example, our recent survey on basket recommendation in grocery shopping offers insights on the importance of users' tendency to repeatedly repurchase previously consumed items, and the challenges of providing users with attractive recommendations of unseen items [19].

Timing. In recent years we have seen an increasing number of publications devoted to complex item set recommendation at venues such as ECIR [e.g., 11, 23], KDD [e.g., 12, 22, 35], RecSys [e.g., 7, 17], SIGIR [e.g., 3, 13, 25, 28, 29], WebConf [e.g., 1, 5, 20], and

WSDM [e.g., 4, 24, 33]. Motivated by the increasing attention from the information retrieval community, we believe the time is right to gather the research conducted in different domains with different approaches together. A tutorial on complex item set recommendation is a perfect opportunity to demonstrate a holistic picture of the research landscape.

2 OBJECTIVES

Our objective for this tutorial is fourfold. First, we aim to introduce the problem of complex item set recommendation and its specific characteristics. Second, we describe the current landscape of research to the audience. Third, we intend to expose our participants to real-world examples of item set recommendation with an invited talk, and to provide them with hands-on experience via a notebook session. Our final objective is to describe open challenges and call for further research in the area, which we hope will inspire both early stage researchers as well as more experienced colleagues.

2.1 Introduction to main concepts

The objective of the introductory segment of the tutorial is to explain what complex item set recommendation is, how it relates to other recommendation scenarios, and what areas it covers. We discuss the main concepts in detail. Our goal is to ensure that attendees get an overall view of the specific challenges of this recommendation sub-field, and the methods currently used in it.

We further discuss the characteristics and the challenges of complex item set recommendation. Specifically, we cover user behavior in creating items sets, focusing on repetition and exploration in interacting with the item catalog in different domains. Moreover, we introduce set representation learning approaches, and discuss similarities and differences with sequence modeling. We further introduce complementarity, exchangeability, and budget constraints as important concepts to consider in complex item set recommendation.

After the introduction, the audience are able to cite a few examples of item set recommendation, and identify whether a given recommendation problem is a complex set recommendation or not. Moreover, they can identify important characteristics of the problem at hand given the specific domain of interest.

2.2 Current landscape of research

In this part of the tutorial, we focus on recent approaches used in complex item set recommendation, ranging from neighborhood-based models to recurrent and graph-based neural networks. We present several representative methods for each domain of complex item recommendation (i.e., grocery shopping, playlist and bundle recommendation), and compare them. Besides, we highlight how existing publications approach considerations of complex item set recommendation, including repetition-exploration, set representation learning, complementary relations, and budget constraints.

We further detail proper evaluation schemes for this recommendation scenario. We introduce new evaluation angles and discuss biases caused by the dichotomy between already seen items and their complementary set in the overall item pool [19]. Furthermore, we also discuss several evaluation metrics that go beyond accuracy including fairness, item exposure, and more.

After this part of the tutorial the audience are able to design models, choose proper baselines and evaluation metrics for an item set recommendation task.

2.3 Hands-on experience with item set recommendation

In this part of the tutorial we move from theory to practice. First, we host an invited speaker from an e-commerce brand that is based in the region (broadly conceived) to share their experiences in complex item set recommendation.

Following the invited talk, we organize a lab session where we first introduce popular public datasets used in the academic literature. Attendees use a notebook to load pre-trained models, and perform recommendation on pre-defined test sets. Attendees are tasked to evaluate the performance of said models by using what they learned in the previous section of the tutorial.

After this part of the tutorial, the attendees are familiar with real-world examples of complex item set recommendation in industry, are able to use the right tools and evaluate their models with the right approach and metrics when faced with a set recommendation problem.

2.4 Future challenges

In this section of the tutorial, our goal is to introduce the various areas and directions for improvement possible for item set recommendation, as well as the main challenges faced by practitioners. We highlight under-explored research directions and call for further research in these areas. Specifically, we point out the importance of new item discovery in areas such as grocery shopping, where relying on previously seen items has been dominant in the literature. Moreover, we discuss taking budget constraints into account when curating item sets, which has been mostly ignored in the literature. Another important direction for future research is societal aspects in this scenario; this includes, for example, ensuring users and items are treated impartially and benefit fairly from complex item set recommender systems, which is a more complicated challenge here than in single item recommendation scenarios because of dependencies in item sets and because of strong propensities for repeat consumption.

We close the tutorial by pointing out related accepted papers in SIGIR 2023 to the audience, followed by a Q&A session.

3 RELEVANCE TO THE INFORMATION RETRIEVAL COMMUNITY

Recommendation has been a constant topic addressed by tutorials in the information retrieval community. Recent examples include graph neural networks for recommendation and adversarial learning for recommendation, WSDM 2022 and ECIR 2021, respectively [2, 10]. Other approaches to recommendation, such as self-supervised learning and causal models, have been topics of tutorials on recommendation at The WebConference and CIKM recently [14, 34, 37]. We are not aware of any prior tutorials on the topic of complex item set recommendation.

At SIGIR 2022, Wang et al. [31] described approaches and challenges in sequential and session-based recommendation. Similarly, we describe approaches and challenges in complex item set recommendation in our tutorial and shed light on future research directions. We believe SIGIR is the most appropriate venue to present this tutorial to the information retrieval community and engage them to conduct further research in this area.

4 FORMAT AND DETAILED SCHEDULE

The tutorial covers seven parts over the course of three hours, in two 90-minutes sessions:

I: Introduction (10 mins)
II: Main concepts (15 mins)
- 1.1 Repetition and exploration
- 1.2 Set representation learning
- 1.3 Complementarity and exchangeability in item sets
- 1.4 Budget constraints

III: Existing approaches (45 mins)
- 2.1 Model architectures
- 2.2 Domain-specific characteristics

IV: Evaluation (20 mins)
- 3.1 Metrics
- 3.2 Going beyond overall accuracy

V: Invited talk (20 mins)
- 4.1 Talk
- 4.2 Q&A

VI: Notebook session (45 mins)
- 5.1 Introducing datasets
- 5.2 Applying with state-of-the-art approaches
- 5.3 Evaluation

VII: Closing (25 mins)
- 6.1 Future challenges
- 6.2 Related papers at SIGIR '23
- 6.3 Q&A

5 TYPE OF SUPPORT MATERIALS TO BE SUPPLIED TO ATTENDEES

We share the following materials with participants:

(1) **Slides:** All slides are made publicly available.
(2) **Notebooks:** We provide notebooks for a guided lab session.
(3) **Pre-trained models:** Model checkpoints are provided to allow attendees to focus on inference and result interpretation during the hands-on session.
(4) **Annotated bibliography:** An annotated compilation of references that lists all works discussed in the tutorial and should provide a good basis for further study.
(5) **Code:** An annotated list of pointers to open source code bases and datasets for the work discussed in the tutorial.

These materials are available at https://irlab.science.uva.nl/teaching/sigir-2023-tutorial-on-complex-item-set-recommendation/

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