Report on the Fourth Workshop on Recommendation in Complex Environments (ComplexRec 2020)

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Abstract

During the past decade, recommender systems have rapidly become an indispensable element of websites, apps, and other platforms that are looking to provide personalized interaction to their users. As recommendation technologies are applied to an ever-growing array of non-standard problems and scenarios, researchers and practitioners are also increasingly faced with challenges of dealing with greater variety and complexity in the inputs to those recommender systems. For example, there has been more reliance on fine-grained user signals as inputs rather than simple ratings or likes. Many applications also require more complex domain-specific constraints on inputs to the recommender systems. The outputs of recommender systems are also moving towards more complex composite items, such as package or sequence recommendations. This increasing complexity requires smarter recommender algorithms that can deal with this diversity in inputs and outputs. The ComplexRec workshop series offers an interactive venue for discussing approaches to recommendation in complex scenarios that have no simple one-size-fits-all solution.

1 Introduction

During the past decade, recommender systems have rapidly become an indispensable element of websites, apps, and other platforms that are looking to provide personalized interaction to their users. As recommendation technologies are applied to an ever-growing array of non-standard problems and scenarios, researchers and practitioners are also increasingly faced with challenges of dealing with greater variety and complexity in the inputs to those recommender systems. For example, there has been more reliance on fine-grained user signals as inputs rather than simple ratings or likes. Many applications also require more complex domain-specific constraints on inputs to the recommender systems.

The outputs of recommender systems are also moving towards more complex composite items, such as package or sequence recommendations. This increasing complexity requires smarter recommender algorithms that can deal with this diversity in inputs and outputs. For the past three years (Bogers et al. [2017, 2018]; Koolen et al. [2019]), the ComplexRec workshop series has offered an interactive venue for discussing approaches to recommendation in complex scenarios that have no simple one-size-fits-all solution.

2 Workshop focus

For the fourth edition of ComplexRec, we narrowed the focus of the workshop and contributions to the workshop about topics related to one of these two main themes on complex recommendation: complex inputs and complex outputs.

2.1 Complex inputs

An important source of complexity comes from the various types of inputs to the system beyond users and items, such as features, queries and constraints. There are active user inputs (interaction), implicit user inputs (task, context, preferences), item inputs (features or attributes) and domain inputs (eligibility, availability). In group-based recommendation, the user input can be a combination of inputs for multiple individual users as well as group aspects such as the composition of the group and how well they know each other. In the context of education for instance, inputs range from the knowledge and skill level of the learner, their preferences for modes of learning, the amount of time available for studying and rehearsing, and the constraints of the location, resources and physical space. These constraints may even conflict with each other or with preferences of different stakeholders.

An additional challenge is providing users with ways to have control over the inputs. For instance by selecting and weighting or ranking user and item features, or providing interactive queries to steer the recommendation. In recommender systems designed to assist customers and troubleshoot problems, or in systems that help office workers with writing reports, one of the inputs is the problem statement, which can be provided in the form of a few keywords, natural language questions, or longer narrative statements. These require increasing levels of natural language understanding to transform into relevant features and constraints that have to be combined with many other types of inputs, including the knowledge and skill level of the person for whom the advice or report is intended.

There are many examples of other domains where recommender systems have to deal with a complex set of inputs, such as:

- *Food*, where there may be dietary requirements, constraints on the availability of ingredients, cooking utilities, time to cook and budget, paired accompaniments such as wine, as well as taste preferences and requirements for cuisine and number of courses;

- *Tourism*, with similar constraints on time and budget, distance, preferences for types of locations, accommodation and mode of transport, as well as inputs related to the travel group;

- *Transportation*, which has to take into account different numbers and types of packages, available vehicles and drivers, as well as constraints from customers being available to receive a package, as well as different priority levels.

2.2 Complex outputs

Another type of complexity that we focused on in ComplexRec 2020 is the complexity of the outputs of a recommender system to move away from a straightforward ranked list of items as output. An example of such complex output is package recommendation: suggesting a set or combination of items that go well together and are complementary on dimensions that matter to the user. In many domains the sequence in which items are recommended is also important. Moreover, different users may want different information about items, so the output complexity goes beyond ranking and also manifests itself in how the interface should allow the user to view the type of information that is most relevant to them. Another example of complexity in recommender systems output are environments where the system's goal is to create new, composite items that must satisfy certain constraints (such as menu recommendation, or recommendations for product designs).

There are many examples of domains where the outputs of the recommender system are complex in one or more of the above-mentioned ways, such as:

- *Food*, where a recommender system could help the users by suggesting a balanced diet by recommending a set of dishes over a longer period, or in composing entirely new dishes based on available ingredients;

- *Tourism*, where travel packages should consist of an optimized, complementary set of locations, accommodations, and activities;

- *Fashion*, where complete matching outfits could be recommended to the user.

3 Format & Topics

ComplexRec 2020 was organized as an interactive, fully on-line, half-day workshop. We encouraged authors to submit short papers and position papers of 4–8 pages in length dedicated to any aspect of recommendation in complex environments. We invited contributions that addressed the challenges associated with constructing recommender systems that must handle complex inputs and/or outputs. These topics of interest for the workshop included, but were not limited to:

- Recommenders with novel complex inputs;

- Recommenders with interesting combinations of inputs;

- Constraint-driven recommender systems;

- Novel knowledge-based recommender systems;
- Novel modes of user interactions with complex inputs;
- Query-driven and interactive recommender systems;
- Algorithms and models that effectively integrate complex inputs;
- Recommending complex items, such as packages and sequences;
- Recommending composite items with complex feature interactions;
- Algorithms for generating personalized items based on feature preferences;
- Novel NLP approaches for dealing with complex inputs and outputs.

Accepted submissions were then invited for short presentations. Evaluation criteria for acceptance included novelty, diversity, significance for theory/practice, quality of presentation, and the potential for sparking interesting discussion at the workshop. All submitted papers were reviewed by the Program Committee.

A total of 6 papers were submitted, of which 5 were accepted for an oral presentation. All papers were reviewed by at least 3 reviewers from the program committee, consisting of international experts in the field. Likely in part due to its online nature, ComplexRec 2020 had a record number of attendees with around 70 participants at the workshop at any given time.

4 Workshop program

4.1 Keynote

The workshop featured a keynote presentation by Christine Bauer, assistant professor at the Human-Centred Computing group at the Department of Information and Computing Sciences at Utrecht University. In her talk "Ratings in, rankings out. Keep it simple, they said. But we need more than that", she reflected on the complexity of recommender systems by reaching out to related fields such as context-aware computing and pervasive advertising for inspiration.

Focusing on contextual aspects as complex input, she demonstrated that there are a huge number of relevant signals to go beyond most of our current "context-aware recommender systems". She proposed to have a view to related fields that deal with context as deeply complex input. In context-aware computing, six years of research provided 3,741 distinct contextual elements for 36 different contextual models [Bauer and Novotny, 2017]. For instance for music recommendation, some of the many relevant contextual inputs are personal preferences, mood, cultural background and how it relates to genres, temporal aspects like time of year (e.g. Christmas or summer) and time of day, purpose (to help relax, motivate to exercise or as background while focusing on work), location (in the car, in Paris), music setup (e.g. type of speakers) and whether you are listening on your own or with others, such as your children, partner, friends, colleagues or students.

On the output side, complexity arises in considering what we want to present, how, for who, and why. A ranked list as output may seem like an appropriate one-size-fits-all solution, but there are many factors that play a role. The appropriate rank cut-off is determined not only on the items in the ranking, but also contextual factors like the device, user preferences and task and how the ranking is presented. Apart from presenting items in a particular order, some items can be highlighted, for instance through distinct colors, icons or moving images, to draw the attention of users. Beyond individual items there are different considerations for item bundles, complementary goods, sequences, repeated recommendations, etc. Completeness is important in recommending items that are part of a whole, like chapters in a book. For some sequences of items, the order is not important (e.g. television series where each program stands on its own), but others it is crucial.

Finally, she drew our attention to what she calls *situationalization* as a dimension next to personalization. Whether recommendations need to be addapted to the situtation can be combined with whether recommendations should be personalized, either to a single user or a group of users [Lasinger and Bauer, 2013; Bauer and Lasinger, 2014].

4.2 Accepted papers

In total, five papers were accepted for presentation and they covered a broad set of complex recommendation scenarios. Moskalenko et al. [2020] presented WikiRecNet, a system for providing personalized recommendations of Wikipedia articles to editors by exploiting the text content and link structure of the articles and built on top of Graph Convolutional Networks and Doc2Vec. Their approach was shown to outperform BM25, CB and kNN baselines. Parra et al. [2020] proposed a transfer-learning model, CuratorNet, based on CNN (ResNet) and trained using BPR for personalized ranking of items from an art store. Their evaluation showed that their model tends to perform better than two baselines. Mavridis et al. [2020] described various challenges and viable solutions for some of the ML-powered ranking algorithms powering Booking.com, with focus on modeling, experimentation and serving. They also show the increase in business value as a result of these considerations. Wadhwa et al. [2020] attempted to predict a user's inclination towards specific price bands using historical user-item, and to use these predictions for creating recommendations to user through re-ranking. Their approach showed improvements in off-line evaluation metrics. Ahlers [2020] discusssed the implications of "smart-city" infrastructure for future developments of recommender systems, such as offering inhabitants to adapt their behaviour, for example in the choice of mobility with personalised options. However, he emphasizes that such a complex recommendation scenario is an as-yet underspecified problem.

4.3 Closing Discussion

The workshop finished with a short plenary discussion that was seeded with the following questions by the organisers:

1. What is the current state-of-the-art in ComplexRec? What has worked well? What is missing and where are the gaps?

2. What are the current key challenges in recommender systems research and practice when dealing with complex scenarios (and more specifically with complex and non-standard inputs or outputs)?

3. What are some emerging domains where complexity in the types of inputs or outputs may require new recommender systems algorithms, designs, or architectures?

4. What are the future potential research directions and challenges in ComplexRec and what should be the focus of future workshops in this area?

Several participants pointed to the need for reducing biases inherent in real-world data as one of the key challenges for not only complex recommendation, but all recommender systems research. Another interesting discussion was related to how complexity is related to the cost of interacting with recommendation: in the case of one-off, expensive purchases, dealing with the input and output complexity becomes more important than in the case of, for instance, selecting which song to play next on a music streaming service. Workshop participants agreed that a better understanding of the relation between cost and complexity would be a valuable direction for future work.

In response to question 3, many domains with complex inputs or outputs were identified that could require new algorithms, designs or architectures. Some of the example domains brought up by the workshop participants included domains with multiple stakeholders, such as education and smart cities; the health/medical domain, with many different personalized restraints, such as privacy, dietary, health, and legal); smart homes, where more and more systems need to be integrated and collaborate with each other; and domains where packages of related items (fashion, cooking) and/or sequences of items (music, travel, entertainment) should be recommended.

One exciting new research direction is recommending new items based on existing features or partials. For instance, recommending new recipes by extrapolating from changes in what is trending, or by taking into account different cultural or dietary requirements.

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The workshop material (list of accepted papers, keynote, and the workshop schedule) can be found on the workshop website at https://complexrec2020.aau.dk/. The proceedings were published as a CEUR Workshop Proceedings volume, available at http://ceur-ws.org/Vol-2697/. The recording of the entire workshop are available on the RecSys YouTube channel at https://youtu.be/nAevW75MzQA.

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