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Editorial

Recommender Systems and Collaborative Filtering

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Recommender Systems (RSs) have become an essential tool for the information society. Their incorporation into everyday life has allowed service providers to alleviate the information overload problem to which citizens are exposed. Every minute, hundreds of hours of video are posted on YouTube, thousands of products are purchased on Amazon, tens of thousands of tweets are published and millions of messages are sent on services such as WhatsApp or Telegram. Recommender Systems (RSs) allow their users to make smart use of this information by filtering out those contents that are irrelevant to them, and promoting those contents that may be of their interest.

In this Special Issue, "Recommender Systems and Collaborative Filtering", we have advanced the state of the art of RSs with new publications in three of its most active research areas: recommendation models, neural RSs and real world applications of RSs. These contributions are relevant and represent a quantitative and qualitative improvement in the development of RSs claimed by society.

1. Recommendation Models

One of the main research lines in RSs is the development of novel models able to capture deeper and subtler information from the data, and to exploit it for offering more accurate and relevant recommendations. Many of these proposals are oriented to improve the heart of the RS, the so-called Collaborative Filtering (CF) method.

Nowadays, the de facto standard in CF-based RS methods is Matrix Factorization (MF). It is based on the assumption that the preferences of users for particular items are characterized by a collection of hidden features, referred to as the latent factors. The MF method is responsible of unhiding these latent factors, of measuring them and, the most important part, of taking advantage of them to provide accurate and relevant predictions. For these reasons, the process of extracting and refining latent factors is a very active research area in RSs.

This Special Issue includes important contributions that provide novel methods for capturing user information in new ways. In [1], the authors propose to include the temporal variable into the equation, giving rise to a time-aware recommender system. Thanks to that, the authors are able to track the evolution of the preferences of users with time, adjusting consequently the latent factors to provide up-to-date accurate recommendations. This is particularly relevant in the domain of music recommendation, where preferences of the users are very mutable and affinities evolve quickly with the prevailing musical trends.

This attempt of providing highly customizable recommendations is a key idea in current RS research. This is based on the well-known fact about RS that they tend to supply 'average recommendations'. For instance, a RS issuing recommendations of movies will always consider that renowned films, like The Godfather, are good recommendations for a user, independently of his/her particular idiosyncrasy. To overcome this problem, in [2] the authors propose a model to

alleviate this 'baseline course' by correcting the implicit bias of the system. For this purpose, the authors formulate a unified baseline estimation model based on the standard deviation of the user's features from the average system's features. This path toward specifically tailored recommendation is also explored in [3]. In this paper, the authors propose to add an extra cognitive layer to the standard predictive model. The task of this layer is to identify similar users according to their cognitive footprint. With this information, the system is able to refine the recommendations to fit better with users' tastes.

This idea of capturing further semantic relations between the users and items of the RS is recurrent in this Special Issue. In [4], the authors propose to import knowledge graphs to RS, proposing a novel model called Neighborhood Aggregation Collaborative Filtering (NACF). It uses the knowledge graph to spread and extract the user's potential interest, and iteratively injects them into the user features with attentional deviation.

In a way or another, this lack of customizability in the CF model is due to the linearity of the underlying MF method. The model produced by MF is essentially linear, which deeply compromises the expressivity of the model. This problem has been addressed in [5], published in this Special Issue, in which the authors propose to iteratively refine the predictions of the MF algorithm. In this way, the standard MF model is tweaked by performing subsequent factorizations that allow the model to estimate the expected suffered error, so that it can anticipate to it and compensate it. This idea mimics recurrent techniques in deep learning, in which the deep architecture allows the first layers to focus on the main features of the data, delegating a finer tuning of the results to the deepest layers.

2. Neural Recommender Systems

Neural Networks (NNs), and particularly deep learning, have been one of the greatest revolutions in artificial intelligence. They allow researchers to provide new and simple solutions to very complex problems. In this vein, the incorporation of NNs to RS has led to groundbreaking contributions to the area, expanding the posibilities of classical RS. In this Special Issue, we have collected some very relevant works in this direction.

A paradigmatic instance of this phenomenon is [6]. In this paper, the authors propose to use a NN to integrate information about consumption patterns of the users, interaction of low and high-order features and time-series information of the habits of the screened users. This leads to a novel model, Attention-Based Latent Information Extraction Network aka ALIEN, which outperforms previous baselines and provides explainability to the recommendations by interpreting the contributions of the different features and historical interactions in the network architecture.

A similar approach can be found in [7], published in this issue. In this work, the authors propose to import deep NNs to the realm of RSs. In this vein, they propose to use Graph Convolutional Networks (GCNs) to improve recommendations to users by analyzing session-based data created from previous interactions with the system. Session graphs are collected from the market data, which are feed to a Convolutional Neural Network (CNN) to estimate the probabilities of each product of being bought in the next purchase.

Nevertheless, the role of NNs in RSs should not be circumscribed to the improvement of the issued recommendations. A hot-topic in RS research is to propose beyond-accuracy quality measures, that is, performance coefficients that provide valuable information about the predicted recommendations different from customary prediction error. One of the most illuminating of these beyond-accuracy measures is reliability, i.e., confidence in the issued prediction. Incorporating trustworthy reliability is one of the most outstanding problems in RSs. With this knowledge, recommendations can be gauged to find a fair balance between novelty and risk. In this line, in this Special Issue we have published [8]. In this work, the authors propose to use deep NNs for providing reliability values on top of the predicted ratings. More precisely, they propose to use a three-level architecture. The first layer returns predicted ratings according to a standard CF-based approach, say MF. These predictions are subsequently processed by a NN that estimates the expected prediction error, a function whose inverse can be interpreted as a reliability. Finally, a third NN layer processes both the predicted ratings

and estimated errors and returns an adjusted recommendation list created by tweaking the prediction accordingly to their reliability.

3. Real World Recommender Systems

Beyond the academic world, machine learning plays an important role in simplifying and aiding people to carry out complex tasks. In this spirit, the interest of the society in the applications of RSs to manage huge amounts of information is on the rise. For this reason, it is crucial to deepen our knowledge on the applications of RSs to real world problems. In this way, a thorough analysis of the pros and cons of the applications of RSs is a very valuable work.

An important current trend in real work RSs is their applications to education. Intense efforts have been put to address problems arising in the educational environment. In this direction, in this Special Issue we have published [9]. In this paper, the authors propose to use RS techniques to sort out open educational resources, so that teachers and learners are able to find high-quality and relevant support material. For this purpose, they compare traditional content-based recommendations with non-personalized recommendations based on pedagogical quality scores of the resources, as well as hybrid approaches. Also in the educational domain, in this issue we have published [10]. In this work, the authors propose a method for filling out the missing values of evaluation tests that a student may skipped. This not only allows teachers to fill the gap when a student cannot attend an exam, but also provides them richer information to decide final marks. Using this method, it is not mandatory that all the students complete all the required assignments; only a small portion of the tasks can be carried out by a student and the other scores are interpolated from the results of his/her mates. For that purpose, the authors re-formulate the problem of predicting marks as a recommendation problem of students against marks, where the ratings are now interpreted as exam scores.

This idea of translating a real world problem into a recommendation problem by means of an appropriate reinterpretation of MF is a recurrent idea in this Special Issue. In [11], the authors propose a MF-based RS for improving the quality of manuscript editing services. This allows the system to automatically recommend an editing expert for a particular task based on his/her expertise, a process that is customary to be carried out slowly and subjectively in a manual way. To this end, the authors propose to code the opinions of the clients about the proofreaders in a binary recommendation matrix and to fill the missing values by means of MF.

Finally, when applied to real world problems, RSs may need to fuse multi-source data to cope with very complex and fuzzy situations. In this Special Issue we have addressed these information fusion approaches based on RS. For instance, in [12], the authors propose to combine MF methods with deep NNs for predicting the performance of software developers in software engineering tasks. For this purpose, the author create a model that uses three MF-driven predictions on similarity of prospective tasks, similarity of developers' skills and task-developer information. With these data, they feed a fusion method that integrates the multi-source data. Through a NN, the system is able to forecast accurately the developer performance, leading to a drastic improvement in the quality and speed of software construction in real companies.

4. Conclusions

In this Special Issue we have pushed the boundary of knowledge in CF-based RSs both from a theoretical and a practical viewpoint. The contributions collected in this volume have aided to extend the known methods and to find novel applications of RSs to improve people's life. The researchers in RSs form a very active community worldwide committed to addressing new and ever-changing challenges, and this Special Issue has been an exceptional witness of this will. We will continue advancing to satisfy the demands of the society of providing new solutions to old problems.

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