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***Abstract*—One of the underlying trends in the research and practical applications of recommender systems shows the direction of the involvement of the aggregated information on both the user and the item side. The essence of group recommendation techniques is to find and identify the latent factors behind the decision of a group. Recommendation methods operating on item sets involve aggregated preference information but on the opposite, the item side. We would like to reflect to this phenomenon by presenting works and practical applications in both of the mentioned cases. To increase the quality of the service and also user engagement, explanations on the recommended items are presented to the user. This technique is typically used in the electronic commerce but alternative approaches also appear in the practice. An item-based explanation technique is also discussed foreshadowing the possible direction of item set based explanations.**

Keywords–group recommendation;item set recommendation;recommendation explanations;location aware;latent factors

I. Aggregation

Initially, recommender systems have been designed to estimate the preference of a specific user over each item in the particular recommendation scenario. To overcome this problem, to mention the most prominent technique, singular value decomposition and other representation learning based methods have been evolved to find latent factors in the taste space of the users. In this case, the latent factors are to be found on the preferences of the individual users on the individual items.

The research on group recommendations showed a considerable progress recently. Group techniques are used for web and news pages, tourist attractions, music tracks, television programs and movies. To mention an illustrative example, group based recommendations typically appear in the context of touristic destinations [1]. Although the typical recommendation scenario is different on each domain, the underlying mechanisms opened a new level of abstraction. In the case of group recommendations, the latent factors cannot be deduced directly based on the user feedback, and additional layer of information separation is to be involved.

In their work, Sharma et al. [2] discuss a recommendation technique operating on item sets. In contrast to group recommendations, analogously to item-item collaborative filtering, item set based recommendation involves information aggregation on the opposite side of the recommendation problem. Thinking about the available information, the task to solve in this case is similar to the group recommendation case, as an additional information aggregation layer is involved into the recommendation scenario.

As discussed above, the phenomenon of information aggregation can be present on both dimensions of the recommendation problem as a binary decision. While the phenomenon of group recommendations can be dated back to 2001 [3], item set recommendations appeared significantly later, in 2010 [4]. Thinking about content marketing in on-line social networks, treating a thematic page followed by users a recommendation scenario, both the user groups and items sets problems are present at the same time. At the moment, predictive models are applied to fulfil the needs of content marketing. An alternative approach could be the application of group recommender techniques on item sets.

Looking at an example in the field of content providing, the application of recommender systems for traditional radio content can be also looked at as a recommendation technique over a set of items. An illustrative example of this domain is discussed by Hirschmeier et al. [5]. To be more exact, in addition to operating with a collection of items, the traditional radio involves several rules of the edited content to be fulfilled by a properly operating radio recommender system.

II. Set Distance

An advantage of the graph based recommender systems is the ability to represent heterogeneous information [6]. Unfortunately, the potential of the graph based techniques is currently undermined. Typical graph based methods are based on a distance measure between two nodes of the graph. In this case, both the number of connecting edges and the parallel paths are involved into the calculation of the recommendations [7]. By defining a distance metric between two node sets, graph based techniques can also be involved in the user group - item set scenario.

To provide an example, spreading activation, a relatively simple technique is discussed as the method is capable to calculate a proximity measure between the nodes of a graph. In a typical scenario, the technique is applied to spread the activation from the node representing the user in question. By specifying the initial activation of multiple nodes of the graph, the distance is to be calculated from a set of nodes. Having the termination criteria of the spreading met, instead of looking at the activation of only one item, the activation of the items in question can be aggregated, thus the distance is to be calculated to a set of nodes. In the case of a concrete recommendation problem, a more appropriate node set kernel over graphs can be involved.

III. Set & Hybrid Explanations

The involvement of the explanations into the presentation process of the recommended items leads to a higher trust and engagement of the end users. According to Kaminskas et al. [8], while it is more straightforward to generate explanations in the content-based case, collaborative recommendations cannot be easily formulated into effective explanations. Kaminskas et al. provide a technique to overcome this problem by discussing item-based explanations.

Thinking about the information aggregation on both the user and the item side, the problem set of recommendation explanations is to be extended by novel challenges. Involving also privacy issues, as the latent factors of user group recommendations (the users) and item set recommendations (the items) are revealed, a question could be what should be presented to the user? Will the presentation of the individual preferences increase user trust and engagement? How the discovered user group and item set preferences are to be presented in an effective way?

Thinking in more general, explanations should be looked at also from the aspect of the hybridization techniques. Regarding the involved information sources, explanations can be generated based on various types of information. For example, research on the representation and utilization of heterogeneous information sources is conducted by Grad-Gyenge et al. [7] also introducing the paradigm of relatedness. The essence of the introduced information representation method is the capability of alloying collaborative and content-based information sources in a graph based knowledge base. The graph is then utilized later by various recommendation techniques. One of the main statements of the paradigm of relatedness is to provide a generalized technique to treat collaborative and content-based information at the same level of abstraction. To summarize it, research in the past shows a trend of generalization of the information source types. Looking at the future of the explanation techniques, the aggregation aspect of the available information can be treated as one of the next challenges.

IV. Location

A potential application of location aware recommender systems can be found at exhibitions in museums. A prominent work in this field conducted by Lanir et al. [9] investigates usage, behaviour patterns, and attitudes of the visitors in the context of a smartphone based, location aware technique. The involved location identification solution strongly determines the accuracy of the information.

Beacon based solutions offer a higher accuracy and also the identification of the visitors. Unfortunately the involvement of such a technique presumes technical skills or equipment leading to an unbalanced sampling of the visitors. WiFi signal strength based location estimation can be a possible solution to overcome this problem. Depending on the actual alignment of the hotspots, the accuracy of such techniques varies between 0.5 and 2 meters. By involving a less accurate but a more practical and cost effective location identification service, the identification of the exhibited works and also the visitors becomes fuzzy. Referring to Section I, this uncertanity probably leads to the involvement of information aggregation both at the user and the item level.

V. Conclusion

The research work conducted by Sharma et al. [2] discuss a recommendation technique on item sets. Working on a recommendation method in the field of radio content, Hirschmeier et al. [5] inherently investigate item set based techniques. In the latter case, user groups are also to be involved based on the broadcasting roots and the use-cases of radio listening. The speciality of radio recommendations is the several constraints on the assembled edited content based on the historical roots of the radio era. Kaminskas et al. [8] present an item-based explanation technique foreshadowing the application of explanations in the case of item sets.

The primary goal of representation learning based recommendation techniques is to find latent factors in the "taste" space of the users where each user is represented by a vector containing the item preferences in its dimensions. To develop the model to represent the information, the preferences are typically available at the individual level both on the user and the item side. To reflect to this methodology, some of the novel directions of recommender systems involve aggregated information, thus the preferences are not necessarily available on the individual level but more in user groups and item sets. The application of the latent factor models are to be altered by introducing additional levels of abstraction similarly how deep learning techniques are organized.

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