

# The Future Directions of Recommender Systems



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Jun 22, 2018 · 4 min read ★

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Helping users handle the issue of information overload was perceived to be the original task of search engines or information retrieval systems, but what makes recommender systems distinct from search engines are the criteria of being “*personalized, interesting and useful*”. In fact, when a user is using a search engine, she knows what she is looking for, and makes the query accordingly. In contrast, recommender systems operate when the user does not know what she wants or likes, but the system knows the user’s tastes; finds items that she prefers.

What makes a recommendation more *interesting* and *useful* is the factor of “*intelligence*”. Intelligence is the key core of personalization to understand the user’s preferences, predict user’s unknown favorites, and at the end provide recommendations beyond a simple search by

matching the query and the content. Recommender systems research has incorporated a wide variety of Artificial Intelligence (AI) techniques including machine learning, data mining, user modeling, and case-based reasoning, among others. The idea of having an intelligent system, which can think and learn like a human, led to more humanized techniques called Computational Intelligence (CI). CI is a branch of AI that explores the adaptive mechanisms to enable intelligent actions within the compound and changing environments.

Yet, there are many unaddressed issues and free rooms to be improved using advanced techniques. For example, deep learning is a promising alternative to the conventional neural networks. In recommender systems, there are many entities and properties assigned to the items and users, finding the proper feature is vital for improving the quality of classification and clustering methods. In recommender systems that involve users' behaviors, the most effective features can be a complex combination of the system properties, which are hard to be extracted and modeled by ANN. Deep learning methods are superior for an effective feature learning, especially when there is no known effective feature. The outcome of deep learning is usually surprisingly unexpected, specifically when there is no supervised class. Modeling and designing recommender systems as online two-sided platforms will benefit from deep learning to effectively learn and predict the strategies of the users and providers enabled by the amount of data provided by the platforms.

Gamification, using the game design and elements in a non-game context, can increase the user's engagement and retention in interactive recommender systems. To promote user experience, the whole system can be designed like a game user-interface or using game-like features such as points and penalties. In a recommender system, the gamification aspects can include, but not limited to, providing points for the new ratings/reviews, competing with the other users in order to get more points, designing the system with interactive objects such as 3D representations and animated characters.

| <i>System features</i>         | <i>Future research directions</i>   |
|--------------------------------|---|
| User-provider participation    | <ul style="list-style-type: none"> <li>– Investigating the economic benefits and business and pricing models of a recommender system</li> <li>– Analyzing which part to be subsidized and which part to be charged (item provider and consumer)</li> <li>– Rewarding users to rate the items</li> <li>– Studying the recommendation quality from users' perspective</li> </ul>  |
| User data/ preference modeling | <ul style="list-style-type: none"> <li>– Managing uncertainties of preference modeling</li> <li>– Extracting implicit information about the users from their daily activities</li> <li>– Storing data in ontology-based repositories and discovering semantic similarities and relations</li> <li>– Exploring alternate options of ranking and recommending items to the users by considering several criteria</li> </ul> |
| System platform                | <ul style="list-style-type: none"> <li>– Utilizing distributed and elastic platforms</li> </ul>   |
| System architecture            | <ul style="list-style-type: none"> <li>– Studying mobile applications and security vulnerabilities in decentralized environments</li> </ul>   |
| Adaptivity                     | <ul style="list-style-type: none"> <li>– Designing a system to operate within dynamic environments and autonomously choose the appropriate recommendation algorithm</li> </ul>  |
| User interface                 | <ul style="list-style-type: none"> <li>– Experimenting visualization features including rating visualization and scale, recommendation sequence, number and justification of recommendations, location of the recommendation on the page</li> <li>– Exploring the gamification possibilities to increase the user's engagement and improve the usability</li> </ul>   |
| Security and privacy           | <ul style="list-style-type: none"> <li>– Analyzing the required amount of user data</li> <li>– Exploring the tradeoff relation between security and privacy to preserve a suitable balance</li> </ul>   |
| System performance             | <ul style="list-style-type: none"> <li>– Exploring user perception by considering user's privacy concerns, experience, knowledge domain and emotional states</li> <li>– Investigating the usability of the system</li> <li>– Studying the criteria interdependencies</li> </ul>   |

In today's market where values are created by users' networks, product and service providers can no longer compete by simply comparing features and prices to gain the competitive advantage. Recommender systems can be empowered with theoretical foundations such as network effect, two-sided market, and game theory. In fact, designing recommender systems as online two-sided platforms will provide a rich source of data (ratings, items, users, etc.) and will open the door to innovations in terms of dealing with data as a commodity. Moreover, as stated by the two-sided market theory, it is enough to induce either the consumers or providers to use the platform of recommender systems, so that the other part becomes motivated to join the platform. The main challenge is to determine the type and amount of incentives to provide to each side (users and providers) so that the other side will follow. In this context, laying theoretical and algorithmic foundations for novel subsidizing and pricing mechanisms of recommender systems is a highly appealing objective.

The inspiring directions, which come with computational intelligence, make this emerging research area more interesting and appealing for further research, development and practice.

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The full-text is published in The Computer Journal by Oxford University Press:

M. Taghavi, J. Bentahar, K. Bakhtiyari, and C. Hanachi, “*New Insights Towards Developing Recommender Systems*,” The Computer Journal, vol. 61, no. 3, pp. 319–348, 1 March 2018. DOI: [10.1093/comjnl/bxx056](https://doi.org/10.1093/comjnl/bxx056)