INTRODUCTION

Motivating customers to purchase products or services is the purpose of marketing and, hence, of marketing with the means of electronic commerce as well. The latter is an Internet-based economic model employing large sets of customer data as key components to make proper business decisions. To support decision making, computerised methods have been and are being developed to help decision makers in considering options, courses of action and implications. There are three major approaches to support decision making by computer-based information systems. Interactive decision support systems aim to assist upper-level decision makers (individuals or groups) in solving problems; they should be easily adaptable or re-designable when the problem environment changes. Expert systems imitate the decision making of human experts utilising knowledge bases, expressed in form of facts and If-Then rules, and inference engines in specific problem domains; they do not only aim to help decision makers such as decision support systems do, but to replace them completely. Finally, recommender systems provide personalised guidance to users based on individual tastes or preferences previously expressed; they are particularly useful to filter through huge data collections overwhelming the users by their sheer sizes.

To select useful information about products or services in huge datasets, the use of recommender systems will be considered in this chapter. They do not only retrieve information from databases like search engines do, but they also filter out suitable data to meet individual interests and special use cases. In 1988, for instance, the book “Touching the Void” by the mountain climber Joe Simpson appeared. This harrowing account near death in the Peruvian Andes received positive feedback from reviewers, but did not sell well. A decade later, John Krakauer released the mountain-climbing tragedy “Into Thin Air”. Having become a publishing success, Amazon.com recommended the buyers of “Into Thin Air” to purchase also “Touching the Void”, which sold very well thereafter. This e-marketing success is due to Amazon’s recommender system that finds patterns in buying behaviour and recommends to the company’s customers books of genres or topics similar to the ones they had purchased before.

The main challenges of the recommender systems’ methodology are how to optimise performance in order to efficiently and accurately recommend products or services, how to deal with incoming users who have not rated any items before, and how to deal with the lack of information prevailing upon initialisation not allowing to draw any inferences. As a way to tackle these problems, we propose the novel concept of consensual recommender systems exploiting social relationships and consensus. The idea behind is that social connections and the corresponding message exchange between users in real-world
networks capture their behaviour, because the users implicitly share their preferences and experiences by interacting and exchanging information. The connectivity within social networks is readily available on currently popular social media, which make intensive use of social connections, and which identify so-called friends by connecting neighbours of neighbours.

Since social connections among users are created on the basis of rating values which are, in turn, derived from models, we consider agreement in each group of a model. To find an agreement between a group’s members, they need to interact with each other on certain quantities of interest depending on their states and, finally, reach agreement by adjusting their mutual decision states. To capture reaching such an agreement algorithmically, Olfati-Saber et al. (2007) discussed a decision-making approach based on a network of distributed agents, whereas we shall focus on the concept of consensus. To this end, the following analogy to multi-agent systems will be utilised: (i) members or users are identified with agents, (ii) multi-criteria ratings of users are identified with the initial-stage values of agents, and (iii) the degree of connection is identified with the concept of preferential attachment in scale-free networks.

Suggested by networked multi-agent systems and the co-operative control problem, where group members need to interact with others to asymptotically reach agreement values, solving the consensus problem means to apply a consensus protocol, i.e. a communication rule to exchange state information between users and their neighbours in order to reach group agreement by means of distributed decision making. The information available to group members consists of the initial decision stage and the degree of connection, which is local to them and their direct neighbours. In other words, consensus protocols are employed to determine agreement points if there are conflicting opinions, which are represented here by different rating values. Among the many possible consensus protocols, the leader-following one is chosen (Sodsee et al., 2010) identifying user preferences with agent states. Based on the members’ trust derived from aspects such as experience, knowledge or popularity in the social network, a leader is identified in each group of followers, who guides the followers’ behaviour with respect to preferences for items – an aspect rendering this approach particularly suitable for marketing purposes.

As algorithmic basis for a correspondingly enhanced recommender system, an incrementally learning collaborative filtering scheme, the algorithm InCF (Komkhao et al., 2013), is combined with the leader-following discrete-time consensus protocol (Sodsee et al., 2010), giving rise to the new algorithm LFC-InCF. In the form of sets of clusters it creates in its initial phase from user-rating matrices behavioural models of the users with similar interest applying techniques from data mining and machine learning. The method uses the degree of membership measured by the Mahalanobis distance and the Mahalanobis radial basis function to identify a cluster as the best match with an input vector joining the system. The algorithm’s incremental learning part either associates an input vector with an already existing cluster as target cluster or includes it into the model being built as a new cluster. Its subsequent recommendation phase aims to classify the characteristics of a consulting user by associating with him or her the closest agreement point in the model having resulted from the learning phase.

The scheme’s extension to be defined and extensively evaluated by experiments later in this chapter takes the social connections of group members expressed by so-called rating-weighted networks into account. Relations between users represented by the topology of scale-free networks are examined. Users are connected into such rating-weighted networks according to the Barabási-Albert model by preferential attachment based on rating values. To find group agreements, the leader-following consensus protocol is applied in order to improve the quality of recommendations to communities. It will be shown that this enhanced algorithm deals well with the new-user problem by identifying leaders in groups, as such leaders provide the highest numbers of item ratings, and current group members influence joining ones. Furthermore, to measure up to real-world phenomena in distributed decision making and to improve the