Swarm intelligence and evolutionary algorithms in recommender systems

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The modern consumer is confronted with a huge selection of goods and services from which to choose. Especially electronic retailers provide a huge variety of choices, options and customization for their products. In such a setting, presenting a consumer with the most appropriate products is not an easy task. This is why many retailers use recommender systems, which provide the user with a personalized set of items that (hopefully) match the user’s taste. Recommender systems are often based on a technique called Collaborative Filtering, which analyzes the past behavior of the user (e.g. ratings of items or previous transactions) and finds the most similar other users through a k-nearest neighbor approach. This neighborhood then provides the needed information to estimate the rating of a previous unknown item through an aggregation (most common is an adjusted weighted sum) of the individual neighbors ratings. Many methods utilize only the ratings of an item and do not use any additional data about the users or the items, such as age, gender or genres in movies. By using this information in the neighborhood building process, a recommender algorithm could find a more similar neighborhood with more like-minded users and therefore generate better and more personalized recommendations. Additionally, these features can be weighted by a computer generated vector, which comprises the personal preferences of each user. We use a method proposed by Ujjin et. al. [1] to generate such weights with a particle swarm optimization algorithm, two variants of a genetic algorithm and an invasive weed optimization algorithm, a novel numerical optimization method. For each algorithm, we propose alternative settings and methods for finding the most useful and satisfying recommendations and compare the algorithms with statistical measures common to the field. Beyond that, we show a parallelized implementation which speeds up the k-nearest neighbour algorithm and look into the problem of unstable feature weights for recurrent independent runs of the above mentioned non-standard optimization algorithms.

References