Abstract

Online platforms use recommender systems to learn user preferences and to recommend personalized items that are likely to be interesting to us. One recommender strategy widely employed is called collaborative filtering. This involves grouping users based on similar preferences and then recommending items users have liked to other users in the same group. One drawback of this technique is that the system fails to make recommendations for new items or new users introduced to the system for which it does not have any/sufficient information. The issue described is known as the cold-start problem.

In order to tackle the cold-start problem, this dissertation investigates the use of Multi-Armed Bandits algorithms for very fast learning which allow us to match the new elements with their respective clusters. To discover the preferences of new users, we show them a series of items that they need to rate. When learning about a new item instead, the goal is to show the item to a sequence of users who can distinguish between the groups in the fastest way possible. How to pick the items to be rated or the users to ask about the new item is a design choice that differentiates between the different strategies used to combat the cold-start problem.

The work is carried out on a standard news dataset and the performance is evaluated against the state of the art approaches that use Decision Trees to map the new elements to their corresponding clusters. The results show that the Multi-Armed Bandit algorithms can be used successfully to find out which clusters the new users belong to and that they generally outperform the Decision Trees approach. The work has also shown promising results when the setup is reversed and the system needs to deal with new items instead of new users.