Tell Me Who I Am: An Interactive Recommendation System

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Abstract We consider a model of recommendation systems, where each member from a given set of players has a binary preference to each element in a given set of objects: intuitively, each player either likes or dislikes each object. However, the players do not know their preferences. To find his preference of an object, a player may probe it, but each probe incurs unit cost. The goal of the players is to learn their complete preference vector (approximately) while incurring minimal cost. This is possible if many players have similar preference vectors: such a set of players with similar “taste” may split the cost of probing all objects among them, and share the results of their probes by posting them on a public billboard. The problem is that

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players do not know a priori whose taste is close to theirs. In this paper we present a
distributed randomized peer-to-peer algorithm in which each player outputs a vector
which is close to the best possible approximation of the player’s real preference vector
after a polylogarithmic number of rounds. The algorithm works under adversarial
preferences. Previous algorithms either made severely limiting assumptions on the
structure of the preference vectors, or had polynomial overhead.

**Keywords** Recommendation systems · Collaborative filtering · Randomized
algorithms · Electronic commerce · Probes · Billboard

1 Introduction

Recommendation systems come up on a daily basis in many human activities, such as
buying a book, renting a movie, choosing a restaurant, looking for a service provider,
etc. Abstractly, one can think of users and objects, and the task of a recommendation
system is to predict which of the objects each user would like. To do that, recommen-
dation algorithms use reports of past experience of the user in question and reports
of others. The key difficulty in making a recommendation is the diversity of opinions
regarding objects. There are many possible sources for such diversity, e.g., differing
personal tastes of humans, different users may not have the same objects accessible
to them, some users may be dishonest, etc. Even when no inherent diversity appears
to exist, various time-variable factors (such as noise, weather, mood) may create di-
versity as a side effect. The main challenge in recommendation systems is how to
overcome diversity: Intuitively, a set of users with similar preferences should be able
to collaborate (perhaps implicitly) by sharing the load of exploring the object space
on one hand, and benefit from sharing the results of their experience on the other
hand. The difficulty is that users do not know a priori which of the other users share
their opinions.

Intuitively, it appears that arbitrary diversity is unmanageable, and one has to make
strong assumptions in order come up with algorithmic results for recommendation
systems. Indeed, most existing approaches restrict diversity somehow, e.g., by as-
suming that most users fall in one of a few “well-separated types,” or by assuming a
simple stochastic generative model for user preferences. Such assumptions are hard
to justify, but superficially, they seem unavoidable. In this paper we present novel
algorithmic tools that show that effective (near optimal) collaboration by coopera-
tive agents is possible even with unrestricted diversity. Our guarantees are relative
rather than absolute: the quality of a recommendation to a user depends on the num-
ber of users with similar opinions. In other words, without relying on any assump-
tion about user preferences, our algorithm provides high-quality recommendations
to users whose preferences are close to the preferences of many other users, while
esoteric users will receive lower-quality recommendations.

Let us first briefly describe the model we study. User preferences are represented
by a matrix where rows represent users, and columns represent objects. An entry
\((i, j)\) represents the opinion of user \(i\) about object \(j\). It is assumed that user opinions
are fixed (i.e., do not change over time), but are unknown to the users at the begin-
ning. In this paper we consider the goal of reconstructing the preference matrix. To