Abstract—Current methods used to explore the possibility of using context-aware ontological semantics for evaluating user-profile similarity are limited. The contributions of this paper are three-fold: a) to utilize and leverage the concept of ontology in p2p-based recommender system, b) to evaluate ontologically expanded user-profile for similarity evaluation, and c) to address the issue of cold-start in p2p-based personalization systems. We evaluated our method using user-profiles, extracted from Netflix Dataset, in measuring similarity between IPTV peer-users. Our method enriches user-profile vector for enhanced similarity evaluation with other peer-users in p2p network. Our approach expands the vector components for similarity evaluation with the other IPTV peer-users’ expanded user-profile. This overall facilitates better comparison, better recommender aggregation, and quality recommendations.

Keywords—Recommender Systems, User profile, Ontology, Collaborative filtering, IPTV.

I. INTRODUCTION

Personalization is an effective approach to respond an IPTV user’s overall interests and tastes. Collaborative recommendation methodologies find IPTV peer-users in a P2P network that can provide content recommendations. These generated content recommendations for a peer-user are based solely on ratings of multimedia items by other peer-users. In such scenario, a user-profile forms the basis of such personalized content recommendation in P2P-based recommender systems. In other words, these systems value user-profile as a true representative for the peer-user’s interests and employ user-profile vector directly for similarity evaluation. Moreover, the growth of ontologies that offer a valuable resource of content descriptors has extended the scale and scope to augment the quality of recommendations generated. In addition, current methods to explore the possibility of using context-aware ontological semantics for evaluating user-profile similarity are limited. To overcome these difficulties, we build a framework component to over existing P2P-recommender system to offer solutions for the above target.

II. SYSTEM DESIGN

A. Architectural Aspect

From the perspective of user-profile sharing among IPTV user-peers, the recommender system follows a P2P network topology. A recommender system can be expressed as a type of information filtering (IF) engine [1] that recommends contents. The system creates a user-profile based on the content viewed by the IPTV user, compares the user-profile with some reference characteristics and finally computes the user’s likeness for a particular content. User-profile information flows from one IPTV user-peer to others. Collaborative user-peers usually have different and diverse tastes. With the distributed recommender system equipped in each user-peer, proper information resources flow from the right source user-peers to the user-peers which need them. After certain data exchanges and evaluation, recommendations can be generated and delivered.

B. Profile Information

3.2 Profile information

Formally, a user-profile can be viewed as a mapping of users and multimedia tags to a set of interest weights

Definition 1: Given a database of users represented by the set $U$ of users where

$$U = \{u_1, u_2, \ldots, u_m\}$$

and a set of multimedia content tags,

$$MCT = \{mct_1, mct_2, \ldots, mct_n\}$$

The profile for a user $u \in U$ is therefore an $n$-dimensional vector of ordered pairs: $u(n) = \{\langle mct_{1}, iw_u(i_1) \rangle, \ldots, \langle mct_{n}, iw_u(i_n) \rangle\}$

where $mct \in MCT$ and $iw_u$ is an interest weight (iw) function for user $u$, assigning weights to multimedia k-tags in MT. The interest weight of a multimedia tag is usually expressed as a numerical value reflecting the user’s level of interest in that item and can be integrated into the user profile which is generally a vector of keywords and weights. In order to calculate peer-user similarity, we represent user profile in the bag-of-words [2] format (BOW format) and use standard approaches such as Cosine, Pearson, Jaccard Coefficient [3] etc to calculate similarity. From above equation, MCT is a vector representing a user-profile class UP and $n = |MCT|$ is number of distinct tags in the user-profile. The $k$th element $mct_k$ in the vector MCT is calculated as follow:

$$mct_k = tf_k \times idf_k$$
$$idf_k = \log_2 \frac{N}{n_k}$$

Sponsors information shall be presented later.
where $t_f$ (term frequency) is the number of times that the $k$th tag in the user-profile class UP. While $id_f$ (inverse document frequency) is the inverse of the percentage of the user-profile classes UPs which contain the tag mct, $N$ is the number of user-profile classes and $n_i$ is the number of user-profile classes which contain the tag mct at least one time. Similarity between two user-profiles is the “displacement” between two profile vectors. For each user $u \in U$, we choose such item tags $mct' \in MCT$ that maximizes the user’s utility. More formally:

$$\forall mct \in MCT, mct'_MCT = \arg \max_{mct \in MCT} \psi(u, mct)$$

In p2p-based recommender systems, the utility of a tag-item is represented by a user-rating that signifies how a specific peer-user liked a particular multimedia item. Similarity evaluation between two peer-users is calculated by traversing the elements in the user-profiles.

### III. SYSTEM EVALUATION

#### A. Similarity Evaluation among peer-users

For evaluation, we use local ontology developed using keywords from Netflix data and later extracted semantic metadata from the developed ontology database (shallow ontology) for semantic enrichment of user-profile. We take a set of around 1750 user-profiles for evaluation. We calculate the cosine similarity between the user-profiles by selecting user-peers. We compute the similarity by using the standard industry-used cosine similarity technique and also by our defined approach. We standardize the results and compute the similarity graphs with different expansion factor $F$. A series of simulation-based experiments validate the efficiency of the proposed model and establish that ontologically enhanced user-profiles of peer-users address cold-start issues as well as offered different recommender peers which can result in superior recommendations. Figures 3.1, Figure 3.2 and Figure 3.3 demonstrate these results.

#### IV. CONCLUSION

We described our work towards a peer-to-peer based system in measuring similarity between peer-users. We expand the user-profile vector component by using ontology. Our ontological scheme improves user-profile process and results in superior recommendations.

### REFERENCES


