Abstract: Recommender System Framework for Heterogeneous Networks

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Social networks such as Twitter, Facebook, and Flickr can be modeled as a *Heterogeneous Network* with multiple node types and different types of relations among them. Recommendation, the personalized provision of items and information, is a key concern for these large-scale information ecosystems where users seek to find new information. These environments provide a wealth of data on which recommendation can be based. However, this information and its associated complexity poses two challenges for recommender systems: (1) the problem of integrating a wide variety of data effectively into a recommendation framework, and (2) the problem of responding to many potential recommendation tasks, because of the wide variety of items present. We have designed the Weighted Hybrid of Low-Dimensional Recommenders (WHyLDR) approach to address the problems of multi-target recommendation and information heterogeneity. [1, 2, 10, 7].

The main idea of *WHyLDR* model is to build a collection of simple recommendation components, each representing a different relation within the data. We combine the recommendation components in a weighted hybrid, and use optimization to learn the optimal weights. In a heterogeneous network there are several relation types , there is a *target relation* that represents the prediction to be made. This target relation can be a direct link of the network or an extended path obtained from walking through different type of nodes. For example in a Movie example the target relation can be $user - movie$ when the desired recommendation task is movie recommendation. However, we can also imagine recommending actors to user. In this case the target relation is achieved by following meta-path $user \rightarrow movie \rightarrow actor$.

WHyLDR components are constructed from two-dimensional projection of n multi-step meta-paths in a network. There are two types of recommendation components in this model, user-based collaborative filtering [6] and item-based collaborative filtering [3], and their formation is guided by the recommendation task. In other to construct the hybrid model, we make use of Particle Swarm Optimization (PSO) [5] to learn weights for each recommendation component in hybrid model. This framework takes advantage of the normalized information gain of each meta-path to filter the less-informative. In addition, the NIG value is used in combination of the component accuracy to predict the weight of each components in weighted hybrid model.

We also demonstrated the utility of extended meta-paths in matrix factorization model of recommendation [8, 9, 11]. We use the multi-relational matrix factorization model DMF from [4], in which different latent feature models are defined for each relation. The NIG can effective measure to omit the less informative meta-paths based auxiliary relations which can either cause over-fitting or increase the learning time of factorization model.

As future work, we are working on weighted meta-path generation using random walk methods to add user rating values to the recommendation framework and measure the effect of those values to recommendation accuracy.

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