Poster Paper

Cluster-based Contextual Recommendations

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ABSTRACT

In this work, we address the problem of contextual recommendations by exploiting the concept of subspace clustering. Specifically, we pre-partition users that have rated subsets of data items similarly into clusters and we associate a context situation with each cluster. The cluster context is defined as any internally stored information that can be used to characterize the cluster members per se. Then, given a query context, we identify the clusters with the most similar context, and we use their members for making suggestions in a collaborative filtering manner.

1. DESCRIPTION

Recommender systems have become indispensable for several Web sites, such as Amazon, Netflix and Google News, helping users to navigate through the infinite number of available choices. Motivated by the fact that often users have different preferences under different context situations, several approaches, e.g., [1], extend recommender systems beyond the two dimensions of users and items to include further contextual information. Context can be defined as any *external* to the database information that can be used to characterize the situation of a user, such as the location, time or companion of the user, or any internally stored information that can be used to characterize the data per se [6]. In our work, we follow an internal contextualization approach, and infer context from the data itself. A simple way to express an internal context is by specifying conditions for the presence of particular attribute values in the data. For example, for a movies recommender, an internal context can be: *genre=comedy* & *production-year=2015*. It is clear that such a context characterization cannot be done upon the whole database, as the data display a lot of variability. Rather, we should look for contextual information in smaller, homogeneous subgroups of the data.

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To extract contextual information, we rely on similarities on the user ratings. Intuitively, users close together in their ratings, share the same context, let it be the preference for similar movie genres, or preferences towards specific directors or actors. Typically the user similarity is evaluated w.r.t. the full dimensional feature space, i.e., all available items. Finding similar users for all different items though is hard, while it is more reasonable to find users similar w.r.t. a subset of the items. A straightforward approach to derive such subsets is to categorize the items based on some domain knowledge. In case of movies, for example, the movie genre can be used and items that belong to the same genre can form a subset. A problem with this approach is that such categories are quite vaguely defined, diverse and also overlapping. For instance, the movies *Ted* and *My big fat Greek wedding* are both classified under *comedy*, the later however can be also found under *romance*. For a user interested in comedies it is not clear whether she would equally appreciate a suggestion on *Ted* and *My big fat Greek wedding*. Such a general item categorization, does not reveal much about the aspects that bring users together. Moreover, such aspects might be beyond some given categorization, like the movie genre and also, they might involve more than one dimension, e.g., movie genre and director. Ideally, we want to find subsets of items which are rated similarly by some users; such a subset implies that these items have something in common which brings these users together. This does not need to be that generic as the genre, but it might be some other common property of the items, like the director, the story, or even a mixture of them.

In [4], we locate such user-item groups by exploiting (fault-tolerant) subspace clustering. Subspace clustering is a popular approach for clustering high dimensional data which discovers, except for the cluster members, the dimensions upon which these members form a cluster. Different subspace clusters might be defined upon different subspaces and member and subspace overlap among the different clusters is allowed. In our case, subspace clustering identifies groups of users with similar behavior w.r.t. a set of items. We employ the items of a subspace cluster to build its context and use it to locate, at query time, clusters with context similar to the query context. In contrast to our prior work [4] that considers all user-related clusters for recommendations, here we define the notion of cluster context and we consider only context-related clusters for the specific user.

Recommendations Basics: Assume a recommender system, where I is the set of items and $\mathcal{U}$ is the set of users. Each item $i \in I$ is described as a set of (attribute, value) pairs; let $\mathcal{D}$ be the set of all distinct (attribute, value) pairs appearing in all data items. For instance, for a movies application, an attribute can be the director or the production year of a movie. A user u might rate an item i with a score $rating(u, i)$ in $[0.0, 1.0]$; let R be the set of all ratings recorded in the system. Typically, the cardinality of I is high and users rate only a few items. For an i, unrated by u, with N_u representing u's most similar users (neighbors), its relevance score is computed as:

$$relevance(u, i) = \frac{\sum_{u' \in N_u} simU(u, u') rating(u', i)}{\sum_{u' \in N_u} simU(u, u')} \quad (1)$$

where the similarity function $simU(u, u')$ evaluates the proximity between u and u'. The most prominent items, i.e., those with the higher relevance, are suggested to the user.

Fault-tolerant Subspace Clustering: Subspace clustering aims at detecting clusters embedded in subspaces of a high dimensional dataset. Clusters may consist of different combinations of dimensions, while the number of relevant dimensions per cluster may vary strongly. A *subspace* S describes a subset of items, $S \subseteq I$. A subspace cluster C is then described in terms of both its members $U \subseteq \mathcal{U}$ and the subspace of dimensions $S \subseteq I$ upon which it is defined as $C = (U, S)$. Typically, subspace clustering does not deal with missing values, which is a key problem for recommendations. Fault tolerant subspace clustering [3] deals with this issue by allowing a certain amount of missing values per items, users and ratings in a subspace cluster.

In [4], we use fault tolerant subspace clustering to locate users with similar preferences to a query user, for computing her recommendations. In particular, for a query user u we locate its similar users via the subspace clusters where the user belongs to. These are locally similar users, the term "locally" meaning that they are similar w.r.t. a set of dimensions (those in their corresponding subcluster). We refine this set of users based on their common ratings to u; this is a "global" evaluation aiming to check their overall proximity, i.e., over all items. This local-global refinement results in a more qualitative set of friends N_u for recommendations. The new set N_u is plugged in Formula 1 for issuing recommendations. Our results show that this careful selection of friends, is reflected in more qualitative recommendations.

Inferring the Cluster Context: We consider that the context of a subspace cluster $C = (U, S)$ expresses the most significant parts of the items S within the cluster; these are captured through the attribute values of the items of S, upon which C is defined and are therefore sets of (attribute, value) pairs. Similar to [5], we ground the significance of each (attribute, value) pair on its frequency in the data appearing in the cluster. By post-processing the (attribute,value) pairs in S, we rank these pairs based on their frequency in C; the significance of a pair is normalized taking into account its frequency in the whole database, so as to downgrade global popular pairs corresponding to common trends and focus on cluster-specific context. This way, we define the context of a cluster as an expression containing one or more significant (attribute,value) pairs. For instance, the context of a movie cluster could be: *genre=comedy* & *actor=Meryl Streep*.

Luckily, our subspace clustering is offline and therefore there is no need to compute at query time the context of the produced clusters. This fact allows us to resorting to non-approximate solutions for context identification.

Contextual Recommendations: Given a user u along with a query with context p, expressed as a set of (attribute, value) pairs with attributes in $\mathcal{D}$, for computing contextual recommendations for u, we first locate the users that exhibit the most similar behavior to u under p. These are the members of the clusters for which u is also a member; we denote them by C_u. Due to the context-constraints though, not all clusters are relevant as some of them describe a different context than p. Therefore, we need a way to evaluate the relevance of a cluster context to p. We distinguish between:

• *Exact context match*: If there are clusters in C_u that match exactly the query context p of u, i.e., C_u^p, then the members of these clusters comprise the set of friends N_u upon which the recommendations for u will be computed.

• *Partial context match*: If there is no cluster with context equal to p, we relax our context relevance evaluation by looking for context-similar clusters, instead of context-identical clusters. To determine how close a context query p and a cluster context c are, we rely on a vector-based approach. Let $\mathcal{D}$ be the set of all N distinct (attribute, value) pairs appearing in all data items. A vector representation of p is a binary vector V_p of size N, whose j-th element corresponds to $\mathcal{D}[j]$. If $\mathcal{D}[j]$ appears in p, then $V_p[j] = 1$; otherwise it is 0. Analogously, the vector representation of a cluster context w is a binary vector V_w of size N, where $V_w[j] = 1$, if $\mathcal{D}[j]$ appears in w; otherwise it is 0. The similarity between p and w is then defined using their vector representations V_p and V_w as:

$$sim(p, w) = cos(V_p, V_w) = \frac{V_p \cdot V_w}{|V_p||V_w|} \quad (2)$$

Having located the clusters C_u^p with the most similar contexts to p, we employ their members as the set of the most similar users to u and compute recommendations based on them. Actually, we apply a weighted ranking approach to refine the set of like-mined users according to the similarity of the context of the cluster they belong to, to p.

Next Steps: We are working on improving our cluster context description, by a better aggregation of the attribute values within the cluster and by using item hierarchies, and on more sophisticated methods for context matching and user aggregation. Also, we are working on the scalability aspect to parallelize the subspace cluster and context extraction parts. Preliminary results with MapReduce appear in [2].

2. REFERENCES

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