Using Embeddings of Line Graph Powers to Retrieve Item Substitutes.

1 Extended Abstract

In order to maximize the performance of a recommender system, a useful capability for a system designer is to be able to understand whether two items are substitutes. Drawing from consumer choice theory [1], substitutes may be perceived by consumers as similar or comparable, such that having more of one product makes them desire less of the other product. Depending on the desired user experience (UX), for a poor user review on a purchased item, the system designer may choose to prioritize the recommendation of a substitute item (with the assumption that the user is still keen on purchasing a comparable item due to its utility), or to deprioritize the recommendation of any substitute item (with the assumption that the user is no longer interested in purchasing any item from the same utility equivalence class). Note that the decision of choosing between these two options is beyond the scope of this work, as it would involve extra data points, such as the severity of the poor user review. In this work, we are interested in using feature learning on networks of behavioral user data to create dense representations that are able to capture notion of item substitution.

One approach of modelling this substitute relationship is to make use of behavioral data mining from impression/click logs. For example, we may extrapolate that item X and item Y are substitutes if we have a large number of user sessions containing impressions on item X and item Y, where the impressions are due to users navigating from X to Y via a "users who viewed X also viewed Y" link. A common inference in e-commerce websites is that these users were comparing X and Y as substitutes. Such links are ubiquitous in e-commerce websites [3]. Heuristics can be built on top of this assumption, however, there is no guarantee how robust they are against the noise that comes from impressions/clicks and data sparsity of long tail items. One principled approach that could fulfill our desired capability, using only behavioral data, was proposed in [4].

A system called Sceptre [2] was proposed to model and predict various relationship semantics between products from the text of their reviews and description. Leveraging topic modeling and supervised link prediction using a collection of metadata features, this system was shown to be performant in various tasks. One task that is related to our work is a specific instance of a link prediction task (call this LPTV), where the a link between two products X and Y is induced by a navigation from X to Y via "users who viewed X also viewed Y". Thus, Sceptre is able to fulfill our desired capability, by learning the semantics of "product relatedness" using product metadata, instead of behavioral data.

In this work, let U be the set of all users, I be the set of all items, and $P = (U \cup I, E)$ be bipartite purchase graph, where there is an edge (u, i), for $u \in U$, and $i \in I$, when there is a purchase of item i by user u. Various node embedding techniques [5] [6] have been shown to be able to summarize relationships between vertices in a graph in the form of dense vector representations. Node embeddings of P can be used to compute top-K item recommendations for a user, by computing the nearest neighbor item vertices in a Euclidean space that are not adjacent to the user in P (i.e., have not been purchased). This simple retrieval method is attractive for the purposes of building industrial recommender systems, as we are able to utilize resilient and distributed system like Elasticsearch [7] to serve the top-K recommendations. For the purposes of retrieving substitutes, however, there is not any guarantee that the nearest neighbor (item) nodes of a user are substitutes of the item(s) already purchased by the user.

In structural graph theory [8], the line graph $L(G)$ of an undirected graph G is a graph that represents the adjacencies between edges of G. Thus, the line graph $L(P)$ has vertices that represent purchases (where a purchase is a user-item pair). Nearest neighbors of a node (a purchase) based on a node embedding on $L(P)$ can be seen as the most related purchases. A natural way to compute top-K recommendations from these embeddings is by returning the list of items that are in nearest neighbor purchases in the node embeddings of $L(P)$ but without an edge to the user in P. However, there is still no guarantee that these are substitutes.

Another concept from graph theory [8] is that of graph powers. The kth power G^k of an undirected graph G is another graph that has the same set of vertices as G, but in which two vertices are adjacent when their distance (the number of edges in a shortest path connecting them) is at most k. In order to see why this concept is useful, we note that two nodes in $L(P)$ that are of distance 3 represent two purchases by two different users of two different items, where the two items are never in the same purchase set of any user. Depending on the underlying marketplace (confirmed typically by UX research), these two items can be inferred as non-complements [1], which makes them reasonable candidates for substitutes. This has drawn us to study nearest neighbors top-K recommendations, computed on the node embeddings on the graph $L(P)^3 - L(P)^2$ (edges are composed of purchases of distance 3), in relation to the feasibility of retrieving item substitutes. To wit, in this work we seek to answer the following questions using node embeddings on $L(P)^3 - L(P)^2$:

1. Can we retrieve item substitutes for a user's purchased item (target purchase) by extracting the top-K items in the nearest neighbor purchases of the target purchase? Does restricting the set of users in the graph to be from the same user segment help in terms of retrieving substitutes for users in that segment?

2. Are we able to solve the link prediction task (LPTV) discussed above, in a performant manner, using the embeddings as features?

An attractive corollary of positive answer(s) to Question 1 is that we will be able to utilize simple retrieval techniques [7] to serve top-K substitution recommendation, and a positive answer to Question 2 implies that these embeddings can be be used in tandem with other features (for example, item metadata) to potentially improve the performance of supervised learning approaches in complex link prediction tasks that include other relationship semantics, such as in [2].

References

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