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Online Transaction Shopping Items Basket Recommender Systems

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Abstract: Recommender systems firstly appeared in the early of 1990s. Since then, even more scientists explore the world of recommender system. Nowadays, recommender system can be found on every big website's company such as Amazon, Netflix and Ebay. In this research work, we focus on state-of-the-art metric that involves recommender systems. The particular metric is the exploration and exploitation of a mathematical function described as weighted support and confidence. The particular metrics have as a primary goal the implementation of them into a recommender system which takes as items into a recommender systems whose similarity metric takes into consideration. According to the aforementioned metrics, results have shown that the mathematical methods will bring important outcomes in data sets such as the ones that can be found on e-shop online websites in recommender systems. This work is part of examination of state-of-the-art mathematical model applied in online stores.

Keywords: Recommender Systems, Transactions, E-shop, Website, Online Transaction Basket Metric, Mathematical Functions

1. Introduction

Recommender system nowadays have shown huge impact into people's online browsing. First of foremost, Netflix prize award of 1 million dollars in in 2006 has launched the publicity of recommender systems. That phenomenon attracted people whose background is in Data Science and Data Engineering to going get involved much more in depth and change their scientific research-wise. Recommender systems firstly appeared back in the 1990s [5, 13]. Nowadays, people live into recommender systems engines on their every day lives. Most of them do not perceive the importance and the involvement of the recommender systems. Big companies such as Netflix, Amazon and Google has made recommender systems appealing and attractive to their audiences since they intuitively and exquisitely placed recommender systems engine onto their own website platforms. The recommender systems are categorized into the model-based and the collaborative filtering ones [7]. Well, starting with model-based recommender systems , these recommender systems implement state-of-the-art algorithms such as Singular Value Decomposition (SVD), timeSVD++ and Principal Components Analysis. In the aforementioned methods the goal is to reduce the dimension of the data and explore features that are hidden from the data, fill in the missing values ones and predict those missing values so that they are ranked and build a top list with the recommended item ones. Nowadays apart from the classic methods which as Matrix Factorization techniques along with the Probabilistic ones, state-of-the-art algorithms coming from the world of deep neural networks have also gotten involved into the recommender engines. The advantages are of paramount importance because the particular ones excel at high performance and offer great top rank list. On the other hand, collaborative filtering methods simple implement similarity or distance metrics accordingly so that they measure based on ratings the similar items from users and examine the case of the user-item correlation. In addition, learning to rank is a case of the recommender systems as a final part before deploying the recommender system engine into production line. I would highly recommend to implement such method. Learning to rank method intuitively and typically examines the top N list of the recommender systems items and changes the list of the items through machine learning techniques. Hybrid recommender systems are also part of the recommender systems engines. In this particular case a hybrid one is a conjunction of collaborative filtering method and a content-based filtering techniques ones. In recommender systems, the ratings shall be done either explicitly or implicitly. There are two types as aforementioned before. Stars, likes, upvotes, downvotes are some of the first category. On contrast, the content-based ones examine the data preprocessing such as extracting information from a comment or a text found on the Amazon reviews. That is exactly because the review description might not respond precisely into the star ratings. For example, TF-IDF is a case in which text is analyzed and examines through metrics the content of the text [3, 9, 10]. So, in next section the related work is described, in section no. 3 the research methodology is examined and in section 4 the conclusion of the paper is summed up.

2. Related Work

Rakkappan L. et al. examined the case of dynamics of contexts and temporal gaps on context-aware recommender systems [15] . In this work, authors deployed a recommender system engine in which neural networks was the architecture in order to train the data and therefore the upside is that the particular stacked neural network outperformed state of the art recommender system in case of sequential modeling. Hidasi B. et al proposed a state of the art Gates Recurrent Neural network so that it approved to outperformed previous state of the art algorithm on recommender systems engines [1, 11]. The particular model is a Recurrent Neural Network in which in which into the hidden state of the unit it weight the learning process. The activation function of the Gated Recurrent Unity is a linear function stochastic process between the previous state and the candidate activation. Experimental results have shown that the GRU method outperformed state of the art algorithms in case on session based recommender systems. Aggarwal Ch. et al. examine the case of techniques of finding actual correlation of the items with one another rather than their level of presence [6]. The particular goal relies on relative measures rather than absolute measures such as support and confidence functions applied to association rules in data sets in which items appear in dense data sets or even they may have negative association rules. Chen W. et al proposed ranking models as a sequence of classifications when defining the essential loss. The particular model has its general implication for ranking and will explore its other issues.

3. Research Methodology

Past research has shown that transactions that consists of set of items that each one belong to each subset [4, 8, 14]. Support metric is a new function proposed which corresponds to the percentage of the number of transactions contained into the database which contatin a set of items as a subset. Based on the this research, my new research methodology is based on a graph theory. Considering that there is an item set which each item that belongs to the item set is connected to one another on edges between the nodes. The weight on the edges depends on the relationship magnitude between the nodes. In case there is no weight between the edges, that means that subject to the relationship, the convention equals to 0. Based on the support metric, we add weight to each edge which is the inverse of the support metric of that pair of items. So, mathematically-wise speaking when the support metric of a pair of items is quite large, the weight of the corresponding edge is small and vice versa [2, 4, 12, 16]. This method is a state-of-the-art method on recommender systems. The particular method is named after basket recommender system. It is efficient on online data collection and processing efficiently for similarity transactions especially on online shopping websites in which there is a similarity on the products based on the context and/or metadata for similarity transactions. The extension of the confidence function found on the same research is th multiplication of the weight that belongs to the item set A plus the support of the item and the relationship that belongs to the item set in B item set plus the total weight of the relationship between the itemsets in A in conjunction with the item set in B divided by the weight that the items in A item set are correlated.

$$support(A, w_i) = \frac{w_i * NoTA}{W * TNoT} \tag{1}$$

$$confidence(A, B, w_i, w_j) = \frac{w_i * NoTA + w_j * NoTB + (w_i + w_j) * INoTAB}{W_i * NoTA} \tag{2}$$

Subject to NoTA = Number of Transactions in which A appears and

NoTB = Number of Transactions in which B appears

NoTAB = Number of Transactions in which A and B appears

INoTAB = Intersection of the number of transaction which appears in A and B

TNoT = Total number of transactions

4. Conclusion

In this research work, we examined the item set transactions into model based ones. The particular work is of paramount importance because the it proposes two metrics which take item set correlations and relationships into consideration. The weighted support and confidence are two metrics proposed in this research work in order to examine and therefore measure the items into a basket based recommender systems on an online website e-shop.

5. Future Work

As a future work, the goal is to examine the proposed extension of the support and confidence methods into a dataset.

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