A two-step model and the algorithm for recalling in recommender systems

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Abstract

When a user finds an interesting recommendation in a recommender system, the user may want to recall related items recommended in the past to reconsider or to enjoy them again. If the system can pick up such recalled items at each user’s request, it must deepen the user experience.

We propose a model and the algorithm for such personalized recalling in conventional recommender systems, which is an application of neural networks for associative memory. In our model, the recalled items can reflect each user’s personality beyond naive similarities between items.

1 Introduction

We propose a new function to give recalled items at each user’s request in standard recommender systems. For example, in a news recommender system, when a user browses recommended news headlines and finds an interesting one, the user may remember articles recommended many days ago. For the user, it might be crucial or simply enjoyable to read them again. If the system can pick up and show such recalled items at each user’s request, it must give the users more convenience and deepen the user experience.

In other saying, our task is to choose items related to an image in each user’s mind stimulated by a given new item. Therefore, the main difficulty lies in the fact that this recalling process is personal and that just similarities between items are not enough.

In a general sense, our recalling is a personal search. There are many studies in the area of personalisation of search engines. For example, it is an important

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issue how to customise searched results based on each user’s activity history ([7]), or how to use user’s memory to help the user’s task in computer systems ([2]), etc.

Such general approaches, however, do not seem proper in our situation since our recalling has it’s own unique character and requirements. Therefore, we should give a simple and effective algorithm in our restricted situation, that is, in recommender systems.

To achieve this, we propose a two-step model of each user’s recalling process in a recommender system. First, for a given item, we extend its features with the information of the old recommendations to the user to construct the recall vector. Next, we pick up recalled items that are near to the recall vector.

Roughly saying, the recall vector is an association or a mental image in the user’s mind stimulated by the given item. The essence of our algorithm is to bring the idea of the classical neural networks for associative memory developed by J.A.Anderson([1]), T.Kohonen, K.Nakano into the space of recommended items to each user.

In the following section, we explain our recalling function and give our model with the algorithm in an abstract way. We discuss the problems in section 3 and summarise our results in the last section.

2 A model and the algorithm for recalling

2.1 the space of items

We suppose the minimum structure of the space of items in recommender systems. All recommender systems have the space of items to be recommended and most of them have descriptions of each item’s properties (characteristics or item profiles) to compare them to each other. The most natural way to introduce such structure is to use a vector space, i.e., the vector space model ([3]). We assume that our system has the vector space model.

Let $V = \mathbb{R}^N$ be the space of characteristics of items; we express each item profile as a point $x = (x_i)_{i=1,\ldots,N} \in V$. More precisely, we have $N$ features to describe the properties, and the $i$th feature of the characteristics $x$ has the weight $x_i \in \mathbb{R}$. We naturally identify an item itself with the characteristics.

We also suppose that the system has a function $\rho : V \times V \to [0, \infty)$ to choose a set $N(x, \epsilon)$ of near items to a given item $x$ and a parameter $\epsilon$ by

$$N(x, \epsilon) = N(x, \epsilon; V) = \{y \in V : \rho(x, y) < \epsilon\}.$$  \hfill (1)

For example, in a document recommender system, the features may be words (tokens or terms), the weights may be defined by TF-IDF algorithm, and $\rho(\cdot, \cdot)$ may be the Euclidean metric $\rho(x, y) = \|x - y\| = \left(\sum_{i=1}^{N} |x_i - y_i|^2\right)^{1/2}$, the cosine similarity $\rho(x, y) = \sum_{i=1}^{N} x_i y_i / (\|x\| \|y\|)$, or others ([6], [5]).
2.2 the two-step model for recalling

Consider a recommender system with the users and the items, which repeats the following procedure. The system recommends an item to each user, who may take the recommendation (buy, read, etc.), or not. It collects the information which items each user took in the past and analyses it to give a new recommendation to each user.

Now suppose that a user finds an interesting item, which reminds the user some items recommended in the past. We call the former item a trigger and the latter recalled items. We propose a function to pick up such recalled items on behalf of the user.

We formulate this function as follows. Let \( R(u) \subset V \) be the set of old recommendations to a user \( u \) and \( t \in V \) be a trigger recommended to the user \( u \). Our task is to pick up recalled items from the set \( R(u) \) at the user’s request. We model this recalling as the following two steps.

First, we extend the trigger \( t \) by the old recommendations \( R(u) \) to get the recall vector \( r = r(t, u) \in V \), which is corresponding to an image in the user’s mind stimulated by \( t \). We explain precisely this part in the next subsection.

Second, we choose a set \( \tilde{N}(t, \epsilon) \) of near items to the recall vector \( r \) by the method \( \rho \) with (1), i.e.,

\[
\tilde{N}(t, \epsilon) = N(r(t, u), \epsilon; R(u)) = \{ y \in R(u) : \rho(r, y) < \epsilon \}.
\]

2.3 the feature relation matrices and the recall vectors

In this subsection, we define the operation to generate recall vectors. Roughly saying, we encode the co-occurrence information of the features of the items in \( R(u) \) into a matrix, and we operate the matrix on the trigger to get the recall vector.

First, we prepare the co-occurrence functions \( c_{ij}(x) : V \to \mathbb{R} \) that depend only on the two elements \( x_i \) and \( x_j \) of \( x \). Roughly saying, \( c_{ij}(x) \) means how strongly \( j \)th feature co-occurs when \( i \)th feature occurs in the item \( x \). The typical examples are a binary type

\[
c_{ij}(x) = \begin{cases} 
1 & \text{if } x_i \neq 0 \text{ and } x_j \neq 0, \\
0 & \text{otherwise},
\end{cases}
\]

or a proportional one

\[
c_{ij}(x) = \begin{cases} 
x_j/x_i & \text{if } x_i \neq 0, \\
0 & \text{otherwise}.
\end{cases}
\]

Second, we define the feature relation matrix \( (F_{ij})_{i,j=1,...,N} \) as the conditional average of the co-occurrence function \( c_{ij} \) when the \( i \)th feature occurs, i.e.,

\[
F_{ij} = F_{ij}(u) = \frac{1}{|C_i(u)|} \sum_{x \in C_i(u)} c_{ij}(x),
\]
where \( C_i(u) = \{ x \in R(u) : x_i \neq 0 \} \) and \( |C_i(u)| \) is the cardinality.

Now, we generate the recall vector of the trigger \( t \) by

\[
r = (r_j)_{j=1,...,N} = n(Ft) = n \left( \sum_{i=1}^{N} F_{ij} t_i \right),
\]

(4)

where \( n(\cdot) : V \rightarrow V \) is a normalising function to adjust the recall vectors to the item space. For example, \( n(x) = x/\|x\| \), or \( n(x) = (s(x_i))_{i=1,...,N} \) with a sigmoid type function \( s(\cdot) \), etc. according to the situation.

Note that this is a similar idea to the classical neural networks for associative memory (the self correlation model) originated independently with Anderson([1]), Kohonen, and Nakano because the essence of our model is to encode the co-occurrence information into a matrix (though we do not necessarily subtract the diagonal elements). We also remark that such co-occurrence matrices (or graphs) are used to select critical features, for example, in some algorithms for search engines ([4]).

3 Discussions

3.1 regression analysis and computational cost

Since \( F_{ij} \) means relations between the \( i \)th and \( j \)th feature, it is natural to consider it as an estimation of a function \( x_j = F_{ij}(x_i) \) and to generalise the linear operation \( F_{ij} t_i \) to an functional \( F_{ij}(t_i) \). However, it is heavy to estimate \( F_{ij}(\cdot) \) by regression analysis or curve fitting with the data set \( \{(x_i, x_j) \}_{x \in R(u)} \), since we have \( N^2 \) functions to estimate. Therefore our algorithm is a quick and simple substitution for such heavy estimations.

Though the order of our algorithm also is \( O(|R(u)|N^2) \) times a cost of calculating \( F_{ij} \), we have the following advantages. First, the cost for \( F_{ij} \) is much smaller. Second, in most of the real applications, almost items have few features compared with \( N \); we can use the properties of sparse matrices since our algorithm skips the weight 0. Third, we can update successively the matrices to reduce the order when each user gets a new recommendation.

3.2 verification of the model

Our model of recalling consists of the two steps: to generate the recall vector as a mental image of a trigger and to pick up the near items to it. Though it seems difficult to verify the model itself, we can test statistically the effectiveness of choosing recalled items in a real recommender system. For example, we can study the difference between the trigger and the recall vector to choose the recalled items, i.e., the difference between \( N(t, \epsilon) \) and \( N(r(t, R(u)), \epsilon') \). The
following asymptotic co-occurrence function $c_{ij}(x)$ with a small parameter $\delta \geq 0$ should be useful for the comparison.

$$c_{ij}(x) = \begin{cases} 
1 & \text{(if } i = j \text{ and } x_i \neq 0), \\
\delta & \text{(if } i \neq j, x_i \neq 0, \text{ and } x_j \neq 0), \\
0 & \text{(otherwise).}
\end{cases}$$

The recall vector $r$ should be also fit for $\rho(r, x)$ to measure how near each item $x$ is to $r$. Though we ensure the adaptation by the normalising function $n(\cdot)$, there is not necessarily a natural one; we may need trial and error with statistical tests in the real system.

4 Conclusion

- We proposed a new function of recalling in recommender systems, which picks up items recalled by a user from old recommendations to the user.
- We proposed a two-step model for the recalling in recommender systems, which consists of generating the recall vector and choosing the neighbourhood in the space of old recommendations to the user.
- We showed the algorithm to implement the function according to our model; the essence is to bring the idea of the classical neural networks for associative memory into item spaces of recommender systems.
- Though statistical tests in a real system are left to the future, a practical implementation of our model should be possible.

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