Related work

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In this research the initial goal was to build an approach to the problem of predicting a time set of labels for a specific user. Moreover, considering this problem in more detail, we have decided that the approaches that are currently used in problems related to recommendations are very similar to ours. Then we decided to delve into the problem of consistent recommendation and the problem of recommending a basket of products to a user or customer in more detail.

In the article [1], the authors show that due to the mechanism of its own attention, SASRec tends to consider long-term dependencies on dense datasets, while focusing on the most recent actions with sparse datasets. This turns out to be extremely important for adaptive processing of data sets with different densities. Using staking blocks with your own attention to identify more complex dependencies between elements. Architecture Bert4Rec [2] is a SOTA solution in its field related to consistent recommendations, so the main feature of this model is the use of bidirectional self-attention to take into account the specifics of the sequence of user actions, which removes restrictions on the ordering of the sequence.

The authors in [3] propose to transform the sequence of recent actions into an “image” in time and hidden spaces and to study sequential patterns as local features of the image using convolutional filters. This approach provides a unified and flexible network structure to accommodate both shared preferences and consistent patterns.

GRU4Rec++ [4] a direct improvement of the 2016 GRU4Rec [5] model from the same authors. The basis of this model is recurrent neural networks applied to the task of consistent recommendation, but, in addition, the authors proposed special loss ranking functions and sampling algorithms, which showed a significant improvement in quality compared to GRU4Rec and made the new SOTA model a solution for 2018. The input sequence of events is converted into a sequence of vectors using one-hot encoding. Next, an additional coding layer can be applied and the result is sent to a sequence of GRU blocks, ending with a fully connected layer to construct a probability vector for the next event.

The authors [6] have made the main focus in this article on the implementation of an algorithm that can take into account the variability of interests over time. For example, a client liked to watch horror movies at some points in time, but at other times he wanted to watch a melodrama. To account for changes in user interests, the authors introduced stochastic representations of client actions. Two vectors are created for the sequence: one describing the average value of the user's interests and the deviation from these values.

In this approach [7], the authors were inspired by the work [1], they decided to add personalization to the recommendation, and they also improved the models to process very large sequences of user data, which surpassed its predecessor in results. RepeatNet [8] combines the usual neural approach to recommendations in the decoder with a new mechanism for repeated recommendations, which can select items from the user's history and recommend them at the right time.

We realized that this area is a bit unsuitable for our problem for predicting temporal sets, but as an option for working in this problem statement, we kept the idea of it. But then we saw an idea that exactly repeats our problem statement, but in recommendation systems. In paper [9] the authors decided to review the methods of recommendations in recent years, of course, most of the methods are based on the application of the transformer model. Here we had an idea. Let's look at a simpler MLP [10] model, which is now quite popular in sequential recommendation tasks, but has not yet been used in next basket recommendation tasks [11]. The article discusses the problem statement, there are examples of datasets that we consider as basic. Also, the main results of the work will be compared with the methods from this article in order to understand how well we work in this area.

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