Model of the Cold-start Recommender System Based on the Petri-Markov Nets

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Abstract. The article describes a model for constructing a cold-start recommendation system based on the mathematical apparatus of Petri-Markov nets. The model combines stochastic and structural approaches to building recommendations. This solution allows you to differentiate recommendation objects by their popularity and impose restrictions on the available latent data about the user.

Keywords: Cold-start, Recommendation System, Petri-Markov Nets.

1 Introduction

A recommender system is understood as a set of algorithms and programs that aim to predict the user's interest in objects (goods, products, services) based on user data, data about the object, and the history of the relationship between objects and users of the system.

Recommender systems are now of great importance in everyday life. Before the advent of the Internet, social networks, or online commerce, people in their preferences were based on their own experience or recommendations of friends and relatives. Now, an opinion about a product or service can be formed based on the reviews of millions of people around the world.

Recommender systems are actively penetrating many areas of human activity. Their role as a defining vector in the system of modern trade and content search for information can hardly be overestimated.

Most of the recommendation systems are based on the analysis of accumulated statistical information about users and objects. The collection of information about user preferences can be done explicitly or implicitly. An example of an explicit collection of information is product reviews and recommendations from users themselves. The implicit collection of information includes a statistical analysis of a typical consumer basket.

Recommender algorithms are divided into two groups:

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- Memory-based. Recommendations are created based on processing the entire available data set. Such algorithms are considered more accurate, but they require significant resource costs.
- Model-based. A model of relationships between users and objects is created, and recommendations for a specific user are already formed based on this model. This approach is considered less accurate due to the impossibility of real-time processing of new data, but it allows calculating recommendations in real-time.

2 Related Work

Most of the recommendation algorithms are based on processing existing user data. One of the main problems of such algorithms is the creation of recommendations for new users, not yet known to the system. This problem is also referred to in some literature as the cold-start problem. It is associated with the lack of explicit information on new users to predict recommendations.

To somehow personalize the user and achieve relevant recommendations, a latent classification of the user takes place based on cookies, demographic and geographic data, Internet activity, and data from social networks [5] [6] [7] [8] [9].

A fairly common approach to constructing recommender systems is the stochastic approach to describing the user-object relationship. Many researchers in their works use Markov chains to build a probabilistic model of recommendations. Thus, in their work, Shudong Liu and Lei Wang [1] presented a self-adaptive recommendation algorithm based on the Markov model, which gives recommendations to users depending on their geographic location. In the article by Mehdi Hosseinzadeh Aghdam [2], a hierarchical hidden Markov model is considered for revealing changes in user preferences over time by modeling the latent context of users. Fatma Mlika and Wafa Karoui [3] proposed an intelligent recommendation system model based on Markov chains and genre groupings. Yijia Zhang et al. [4] integrated social networks and Markov chains in their work to create a recommendation in a cold-start.

3 Proposed model

In our work, we propose to use the mathematical apparatus of Petri-Markov nets to build a model of a recommender system in a cold start. This will combine the stochastic and structured approach to building recommendations. The Markov process allows one to differentiate the popularity of recommendation objects. Petri net makes it possible to impose restrictions on the recommendation net in appliance with the available latent data of users.

Petri-Markov nets (PMN) is a structural-parametric model defined by the set [10]:

$$Y = \{P, M\} \tag{1}$$

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where P is a description of the structure of a bipartite graph, which is a Petri net; M is a description of the parameters imposed on the structure of P and determining the probabilistic and logical characteristics of the PMN.

The structure of the PMN allows combining the Markov probabilistic model of recommendations and the Petri net, which will allow formulating the conditions for developing recommendations for a specific user.

The PMN structure is characterized by the set:

$$P = \{X, Z, I_X(Z), O_X(Z)\} \tag{2}$$

where $X = \{x_{1(x)}, \dots, x_{j(x)}, \dots, x_{J(x)}\}$ is a finite set of places of the Petri net that simulate the initial conditions, categories, and objects of recommendations;

$Z = \{z_{1(z)}, \dots, z_{j(z)}, \dots, z_{J(z)}\}$ is a finite set of Petri net transitions that simulate the conditions for choosing a recommendation object;

$I_x(Z) = \{I_x(z_{1(z)}), \dots, I_x(z_{j(z)}), \dots, I_x(z_{J(z)})\}$ is the input transition function;

$O_x(Z) = \{O_x(z_{1(z)}), \dots, O_x(z_{j(z)}), \dots, O_x(z_{J(z)})\}$ is the output function of transitions;

$J(x)$ is the total number of places;

$J(z)$ is the total number of transitions.

In the context of the task of building a model of a recommender system:

- set places $X = \{x_{1(x)}, \dots, x_{j(x)}, \dots, x_{J(x)}\}$ can be represented by the mathematical similarity of the category, subcategory, or object of the recommendation;

- set transitions $Z = \{z_{1(z)}, \dots, z_{j(z)}, \dots, z_{J(z)}\}$ simulate a refined choice of a category or a recommendation object.

The Petri net P determines the structure of the PMN, and the random process M is superimposed on the structure of P and determines the probabilistic characteristics of the PMN.

The parametric aspects Petri-Markov nets are described by the following set:

$$M = \{q, p, \Lambda\} \tag{3}$$

where $q = \{q_{1(z)}, \dots, q_{j(z)}, \dots, q_{J(z)}\}$ is the vector of transition triggering probabilities;

$p = [p_{j(x)j(z)}]$ is the probability matrix;

$\Lambda = [\lambda_{j(Z)j(X)}]$ is a matrix of logical conditions, the elements of which are equal to

$$\lambda_{j(X)j(Z)} = \begin{cases} L\{\sigma[x_{j(x)} \in I_x(z_{j(z)}), z_{j(z)}]\}, \mathit{if}\ \ x_{j(x)} \in O_x(z_{j(z)}); \\ 0, \mathit{if}\ \ x_{j(x)} \notin O_x(z_{j(z)}); \end{cases} \tag{4}$$

The function L is a logical function that allows the execution of half-steps from transitions to states by the structure of the Petri net. $\sigma[x_{j(x)} \in I_x(z_{j(z)}), z_{j(z)}]$ is the half-step, which is defined as a logical variable that takes the values

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$$\sigma\left[x_{j(x)} \in I_x(z_{j(z)}),\ z_{j(z)}\right] = \begin{cases} 1, \text{ if a half-step from place j(x) to transition j(z)} \\ \text{is performed} \\ 0, \text{ if a half-step from place j(x) to transition j(z)} \\ \text{is not performed} \end{cases} \tag{5}$$

Half-step $\sigma_{i(x)j(z)} = \sigma\left[x_{i(x)} \in I_x(z_{j(z)}),\ z_{j(z)}\right]$ or $\sigma_{j(z)i(x)} = \sigma\left[z_{i(z)}, x_{i(x)} \in O_x(z_{j(z)})\right]$ is called switching the state of PMN, in which from place $x_{i(x)} \in I_x(z_{j(z)})$ they get to the transition zj(z), or from the transition zj(z) they get to place $x_{i(x)} \in O_x(z_{j(z)})$. Two consecutive half-steps form a step.

Graphically, PMN are depicted in the form of oriented weighted digraph. Places are indicated by circles. Transitions are indicated by a bold line. The possibility of performing a half-step is indicated by an arrow.

Let's explain the approach to modeling using a small example of an online toy store. In Fig. 1 shows the model of recommendations based on the application of the Petri-Markov nets.

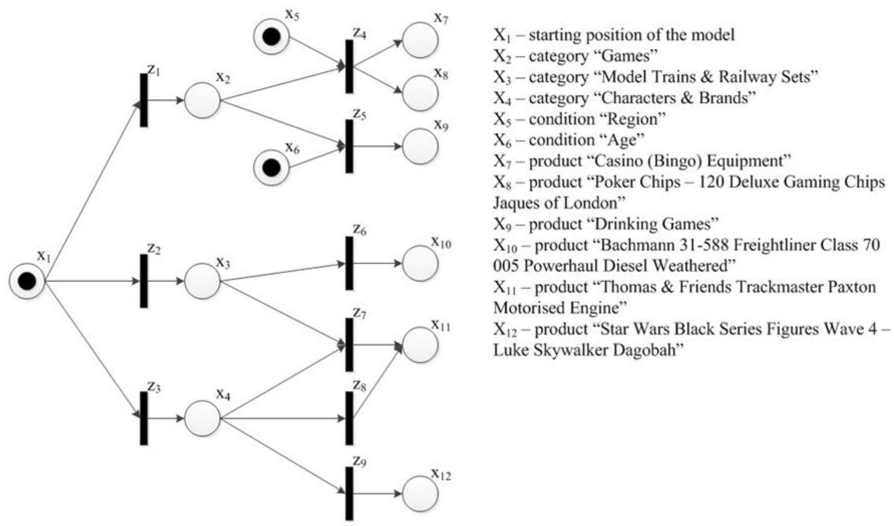

Fig. 1. An example of a recommendation model based on a Petri-Markov nets.

The place X_1 defines the starting place of the model with the marker set. Let places X_2, X_3, X_4 represent product categories ("Games", "Model Trains & Railway Sets", "Characters & Brands"), and places $X_{7,}$ X_8, X_9, X_{10}, $X_{11,}$ X_{12} are products from the corresponding categories. Z transitions determine the probability of transition from one place to another. The probability of a transition being triggered is determined by the popularity of the category, subcategory, or the product itself among other users of the system.

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Places X_5 and X_6 model additional conditions for triggering transitions. Markers in these places are set based on the analysis of latent information about the user. For example, place X_5 can be a geographic or regional condition for selecting items from places X_7 and X_8. And the marker in place X_6 can be an age restriction for triggering the transition Z_5. Then the objects corresponding to the X_7, X_8 and X_9 places will be offered as recommendations only if there is a marker in the place X_5 and X_6.

The proposed model combines various product classifications. The product corresponding to position X_{11} can be recommended both as a character of the popular cartoon "Thomas & Friends" and as a functional model of the steam locomotive "Thomas & Friends Trackmaster Paxton Motorized Engine".

4 Conclusion

The proposed model of the recommender system differs from the existing ones in that it combines the structural and probabilistic approaches to the construction of cold-start recommendations by using the mathematical apparatus of Petri-Markov nets. The model allows one to describe the complex structure of the classification relationships of recommendation objects and combine it with a probabilistic model of object selection.

The model allows:

- take into account a priori user data for making recommendations, which allows you to personalize the search model based on latent data from cookie files, data from social networks, etc.;
- to issue different recommendations to users each time due to the probabilistic model of triggering the transitions of the Petri-Markov nets;
- describe the complex structure of the classification relationships of the recommendation objects;
- to form a choice of recommendation objects by their popularity among other users of the system.

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