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Application of Transfer Learning in Task Recommendation System

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Abstract

In order to meet the need of individualized learning, the current network teaching platform all bring in recommendation system, including the recommendation of learning resources, the recommendation of task and exercise, etc. Problems like outdated datum or sparse datum still exist in teaching platform recommendation. Take task recommendation system of computer courses as an example, the computer knowledge updates quickly. The old knowledge will be out of date in two to three years. Another case is that, when the website was put into use, as the website traffic is quite low, the datum of task finished by the students are quite little. Both of those two cases can cause sparse datum of task system in network teaching platform. In order to solve this problem, this article tries to apply transfer learning into network teaching recommendation system, and verify its feasibility through experiment.

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*Keywords:*Transfer learning; Recommendation system;Mean Absolute Error; Root Mean Squared Error

1. Introduction

Transfer learning, as the name suggests, means transferring the model parameters that have been trained well into new models to help the new models to train data set. The promotion of transfer learning research is based on such a fact, people will consciously use the knowledge that they learnt before to solve new problems more quickly and better. The notion of transfer learning was first officially introduced in the field of machine learning and data mining in NIPS-95 special session on “learn to learn”. “Learn to learn” hopes to achieve life-long study; it hopes that the knowledge learnt before can be used in the following cognitive learning.   After NIPS-95 session was convened, the notion of transfer learning began to attract more and more researchers’ attention. The academia emerges all sorts of researches about transfer learning. Those researches include multi-tasks learning, life-long learning, knowledge transfer, contextual learning, etc.

Transfer learning can be applied widely, transfer learning can be applied in natural language processing, in the literature [Jone B,etal,2006], transfer learning was used to solve the problem that the known sorted training data

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processed by the natural language was too sparse , transfer learning was also applied in Text Categorization, in [Rajat R,etal,2006], transfer learning was applied to construct priori probability, the field knowledge was encapsulated in this parameter. According to the above experience, in order to solve the problem of outdated data or sparse data in teaching platform, this article applies the transfer learning in recommendation system to solve the data sparsity problem in teaching platform recommendation system. Take the basic computer courses as an example, the computer knowledge updates quickly, basically, it updates every two or three years. When the network teaching platform has been used for a long time, the early datum have been out of date, for example, the operating system learnt several years ago was WINDOWS XP, but now the system is WINDOWS 7, the early task exercise datum based on WINDOW XP was insignificant in data mining of recommendation system. Another case is that when the website was first put into use, as the web traffic is quite low, the data of task finished by the students are quite little. The application of transfer learning has thus become one of the methods to solve these problems.

2. Algorithm of transfer learning

There exists a resource mismatching phenomenon in network teaching platform. Some curricula were offered for long and the exercise platform was busy, with large traffic and huge datum of users and exercise. While some curricula are newly offered, and these curricula's task websites seem lonely and quiet. The datum of users and exercise are relatively few, which results in inconspicuous effect of recommendation system of these websites. In order to solve the problem of sparse datum, we propose a solution, which combines transfer learning and network exercise recommendation system. As network exercise recommendation system use complete packet of the users and exercise to recommend, thus, the transferring contents of transfer learning are the completion record of the users and exercise, but the datum in the intensive data set and sparse data set have different distribution, the exercise completion record cannot be directly transferred. This article assumes that the users class and exercise class in network teaching platform have certain tendency of completion exercise, and the relation of the users class and exercise class can be shared in network teaching platform of some extended. We use the relation which represents class to transfer similar but different curricula in network teaching platform.

This article adopts transfer learning method proposed in [Bin Li,et al,2009] to transfer knowledge. This method is based on the thoughts of feature representation transfer to gain the grading pattern of users class and exercise class in source field, and apply this relation to destination field to improve the extended of data sparsity. This algorithm has two steps. 1. Compress the grading data in source field into concise type-level grading model representation which contain effective information, which is called codebook Construction 2. Extend codebook and reconstruct destination field datum, which is called Codebook Transfer.

2.1. Codebook Construction

Codebook construction needs to use collaborative filtering. Recommendation based on collaborative filtering has such a hypothesis, users with similar backgrounds (such as similar majors, in the same grade, similar predictive scores) or with exercise of similar property (exercise with many procedures to operate) generally have similar behaviours. Thus, we can cluster the users and exercise to get corresponding users class and exercise class. In this way, users exercise completion record in network teaching platform can be more concisely shown in a form of exercise completion data with high-levelled user class exercises class.

Ideally, if the users and exercise of the same class have the same tendency to the class, then we only need to choose a group of the users and exercise from each users class and exercise class to construct. However, in real, the users and exercise of the same class are not identical to the tendency of the class. At this time, we usually use class centre point as the prototype of each class. This article adopts orthogonal nonnegative matrix triangular factorization algorithm proposed in [Ding et al,2006], as shown in equation inequation (2.1), to get U matrix of user and users class, and matrix V of exercise , exercise class. After that, construct codebook according to equation (2.2).

$$\min_{U\geq 0, V\geq 0, S\geq 0} \| X_{aux} - USV^{\top} \|_F^2 \ \text{s.t.}\ U^{\top}U = I, V^{\top}V = I \qquad (2.1)$$

$$\mathrm{B} = [U_{aux}^{\top} X_{aux} V_{aux}] \oslash [U_{aux}^{\top} II^{\top}{}_{aux} V_{aux}] \qquad (2.2)$$