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Review Article

Smart Recommendation System Based on Understanding User Behaviour for Afan Oromo Language with Deep Learning

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Abstract: Recommender system is an encouraging technology for enterprises to present personalized suggestions to their customers. But this technology suffers from sparsity problem. In addition, greatest researches are grounded on explicit rating. But most users do not spend time for rating of products. Therefore, this research proposes an effective recommendation based on user behavior Consumer behavior is one of the most important issues that have been discussed in recent decades. Organizations always want to understand how consumer makes decisions so that they can use it to design their products and services. Having a correct understanding of the consumers and the consumption process has many advantages. These advantages include helping managers make decisions, providing a cognitive basis through consumer analysis, helping legislators and regulators legislate on the purchase and sale of goods and services, and ultimately helping consumers make better decisions. Here is a solution for recommending goods based on the users' past behavior over deep learning. The architecture expressed for deep learning is trained by users' past behavioral data. Amazon data was studied and the results indicated that the proposed method has a much higher accuracy than similar methods. Primary contribution is implementation of a user behavior-based recommendation method that discovers interest of users based on implicit rating of product attributes. In addition, this approach uses sequential pattern of purchasing to improve the quality of recommendation.

Keywords: Recommendation Systems Deep Learning Users' Behavioral Afan Oromo

1. Introduction

The rapid and growing spread of information provided on the global Internet network has faced users with numerous and notable problems regarding the resources and information they need, and it is possible that without proper guidance, users make mistakes in making right decisions or choosing the goods and services they need, which will have many consequences, including dissatisfaction, discouraging users and customers from the websites on the Internet. Hence, there is a need for tools and systems to help users choose the right information they need. In recent years, to meet these needs, recommendation systems have been proposed and developed, and there are a variety of different algorithms, articles and scientific texts in this field. Meanwhile, the creation and expansion of social networks, trust networks, and the existence of a variety of relationships among the users of these networks have opened a new horizons to researchers and developers of recommendation systems so by utilizing the social sciences and psychological sciences dominant in these networks, and in particular the existence of a trust relationship among users, they can introduce a new generation of recommendation systems called "trust-based recommendation systems". These systems are able to provide a greater percentage of users with the right answers, and their results are more accurate. Here, we have tried to give suggestions of items to the users considering their behavioral past. Here, the relationship between users and items is created graphically, and according to the graphic theorem, there are suggestions that exactly depend on the behavioral background of the users, hence the users will respond positively to the suggestions with a much greater desire. In the proposed approach, deep learning has been used that leads to high accuracy of the proposed method.

2. Recommendation Systems

Recommendation systems try to suggest the most suitable items (data, information, goods, etc.) by analyzing the behavior of their users. This system will help its user get closer to their target faster within a massive amount of information. Some consider recommendation systems same as a group refinement [3]. Recommendation systems are systems that help users find and select the items they want. It is natural that these systems are not able to suggest without having adequate and right information about the users and their intended items (such as movies, music, books, etc.); therefore, one of their most basic goals is to collect various information in relation to tastes of users and items available in the system. In addition to the implicit and explicit information, there are some systems that use personal information of users. For example, the age, gender, and nationality of the users can be a good source for knowing the user and making suggestion to him. This kind of information is called Demographic Information that a group of recommendations systems are based on this information. With the advent of web 2 and the expansion of social networks in recent years, researchers have found another information source to improve the quality of the suggestions, which is the same information on social networks, and based on this, much research work has been done in this field [1, 2].

3. Principles of Recommendation Systems

There are some things that need to be addressed and, in the design, and implementation process of the system they should be considered in order to establish an efficient recommendation system. They are as follows:

1. The type of data in the system context
2. The filtering algorithm used
   a. Collaborative Filtering
   b. Content-based Filtering
   c. Social-based Filtering
   d. Knowledge-based Filtering
   e. Context-aware Filtering
   f. Hybrid Filtering
3. The technique used to suggest
4. Expected scalability of the system
5. Optimal system performance
6. Quality of the presentable results

4. Related Works

In 2011, Ying Hei provided a model from combining the item-based method and the Bayesian method that could solve the problem of the rating matrix privacy to some extent. For his model, he used the content data of the item and the rating matrix [4]. In the article have argued the need to set personal recommendation systems in learning-enhancing technology for a specific learning feature, rather than using recommendation systems for other areas [5]. In this work, specific learning needs were defined and it was concluded that such personal recommendation systems should focus on learning objectives, learner characteristics, and learner groups, ranks, learning ways, and learning strategies for better recommendations. In fact, the purpose of this article is to provide the appropriate techniques for building a personal recommendation system for lifelong learning. In this article, memory-based methods are used, such as: collaborative filtering that includes context-based techniques and hybrid techniques. In the collaborative filtering method, items used by similar users in the past are recommended. The method of content-based techniques recommends options similar to those that users preferred in the past. In the hybrid technique, both techniques are used to provide more precise recommendations. In this paper the problem of finding a time expert based on meaning is presented to identify a person with specific expertise for different time periods [6]. In this regard, this paper has proposed the development of a time modeling method for the TET issue based on the STMS method, which can provide expert ratings in different groups in an unmonitored manner. This method was inspired by a previous ACT model that was inspired by a separate document (sub-group) (without the conference effect) and developed to all conference journals from the “whole group” of the conference (the conference effect). In the paper the problem of finding the expert in the community of questions and answers (CQA) is studied [7]. The goal of finding an expert in the CQA is to find users who can provide a large number of high-quality, complete, and reliable answers. For this reason, a probabilistic model sensitive to topic is suggested for finding experts in this paper. In the CQA, there are a set of users in the community, first the topics that are interesting to users within the community are automatically found by analyzing the content of the questions they are asked or they answered, and then, based on the topics found, question-answer relationships sensitive to topic can be constructed between questioners and respondents.

This, in its turn, makes it possible to calculate the outstanding score of expertise by considering both the link structure and the topic similarity between the questioners and the respondents. Accordingly, a probabilistic model is made for ranking the candidate experts with the consideration of the user’s expertise and credibility. In expert knowledge has been applied to build a solution recovery system and to find expert and problem-detecting [8]. In order to change the expert knowledge and the base knowledge of a solution recovery system, the idea of developing a recovery system based on the RCBR and RBR combination method that uses CBR is proposed in this paper. Article examines a content-based collaborative recommendation system [9]. In the content-based collaborative system, efforts are made to suggest a specific user the similar options to those that were previously interesting to him. While in the collaborative recommendation system, users with similar interests are identified, and same options are recommended to them. The method used in this article, called fab, is derived from combining these two methods, and is part of the Stanford University Digital Library Project.

Trust in recommendation systems has been discussed and evaluated in [10]. Some authors have argued that traditional emphasis on user similarity may be exaggerated.

This paper proves that traditional factors play an important role in guiding recommendations, and especially the trustworthiness of users should be considered as an important point. To this end, two computational models of trust are presented and illustrated that how they can be used to combine with the standard collaborative filtering frameworks in a variety of ways. In fact, the goal in this article is to improve the collaborative filtering method.

In paper Lee et al. provided a social recommendation system that could create personality product recommendations based on similarity of preference, trust, and social relationships [11]. The Advantage of the proposed method in this paper is comprehensive evaluation of that from the resources recommended.

Recommendation systems based on the multi-meaning value theory are suggested to deal with issues of existing recommendation systems, such as the problem of cold start and change of settings.

In paper Scholz et al. state that existing MAVT-based methods are not suitable for measuring the weighting of attributes to purchasing tasks that are used for common recommendation systems [12]. Learner systems are often used by consumers who are not familiar with the features and scopes available, and are eager to save time and effort. In contrast to this background, in this paper a new approach is developed based on a product configuration process that is devoted to the features of these decision-makers.

5. Proposed Method

In the present era, in many cases, machines have been replaced by humans, and many of the physical work done by humans in the past is carried out by machines today. Although the power of computers in storage, data recovery, and office automation is undeniable, there are still some things that man has to do himself. But in general, machine related issues include systems in which, due to the complex relationships between components, the human brain is incapable of mathematical understanding of these relationships. The human brain can over time detect system habits by observing the sequence of system behaviors and sometimes testing the result obtained by manipulating one of the system components. In the proposed method, deep learning is used, which can be considered as a more advanced state of the multi-layered perceptron neural networks, which has much higher layers. The proposed method focuses on users' general behaviors. Behaviors obtained through binary relations between the user and the objects. Here we formulate the user behavior so that we can extract the rules from it. Flowchart of the proposed method is shown in Figure 1.

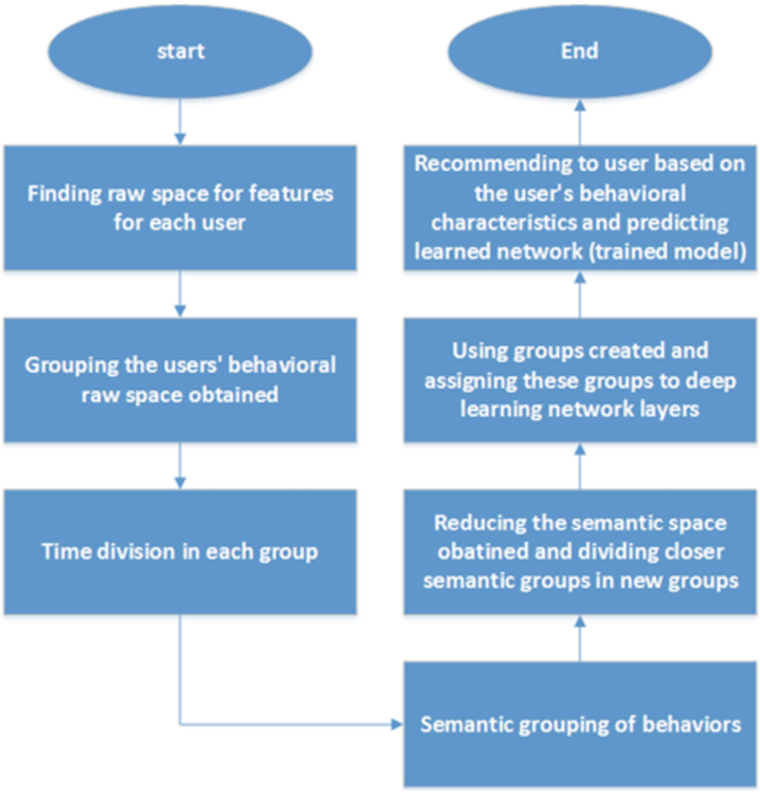

Figure 1. *Flowchart of the proposed method.*

6. Evaluating the Proposed Method

In this section, the proposed method is evaluated. Implementation is done in Python 2.7, and here tensor flow-Gpu is used that uses the gpu to perform computations, so we need a graphic card of over G10. The system used here has the following characteristics:

1. Windows 10
2. 16G Ram
3. NVIDIA 900-52401-0020-000 GRID K1 16 GB Graphics Card

6.1. The Oromo Language

Afaan Oromo (literally Oromo mouth) or the Oromo language, belongs to the Cushitic branch of Afro-asiatic language phylum (languages of Africa), which is reckoned to be divided into six major branches or families. The Cushitic branch itself is divided into a further four groups of North, Central, South and East and Afaan Oromo is one of the languages of Lowland groups within the East Cushitic group.

According to Gene Gragg, Afaan Oromo is probably the third-most widely spoken Afro-asiatic language in the world, after Arabic and Hausa). At this time afaan Oromo is the official language of the regional state of Oromia (the largest regional state in Ethiopia) being used as a working language in offices, educational language for all non-language subjects in junior-secondary schools and it is candidate to be working language of federal government. With regard to the writing system, “Qubee” (Latin-based alphabet) has been adopted and became the official script of Afan Oromo since 1991. This writing system was adapted largely from the fact that its characters do explicitly represent the vowels and the consonants of a language.

6.2. Afaan Oromo Writing System

Afaan Oromoo language uses latin based script called Qubee, which has been adopted and become the official script of afaan oromoo since 1991. The afaan oromoo writing system is a modification to latin writing system. Thus, the language shares a lot of features with English writing with some modifications The Afaan Oromoo writing system of the language is known as “Qubee Afaan O romoo”is straight forward which is designed based on the latin script. Thus lettes in the English language are also in oromoo except for the way it is written. Afaan Oromoo is a phonetic language which means that it is spoken in the way that is written. Unlike English or othe latin base languages there are no skipped or unpronounced sounds or alphabets in the language [15].

The Qubee Afaan Oromoo writing system has 33 letters that consist of all the 26 English letters with an addition of 7 combined consonant letters which are known as “Qubee Dachaa”. These include ch, dh, sh, ny, ts, ph and zy. All the vowels in English are also vowels in “Qubee”. These are a, e, o, u and i. Vowels have two natures in the language and they can result in indifferent meaning. The natures are short and long vowels. A vowel is said to be short if it is one. If it is two, which is the maximum, then it is called a long vowel. Consider these words: lafa (ground), laafaa (soft). In a word where consonant is doubled the sounds are more emphasized. For example, dammee (sweety), dame (branch

6.3. Afaan Oromo Punctuation Marks

Punctuation is placed in text to make meaning clear and reading easier. Analysis of Afaan Oromo texts reveals that different punctuation marks follow the same punctuation pattern used in English and other languages that follow Latin Writing System. Like English, the following are some of the most usually used punctuation marks in Afaan Oromo language (Tariku, 2017).

1. “Tuqaa”, Full stop (.): Like English full stop is used at the end of a sentence and also in abbreviations.
2. “Mallattoo Gaafii”, Question mark (?): is used in an interrogative or at the end of a direct question.
3. “Rajeffannoo”, Exclamation mark (!): is used at the end of command and exclamatory sentences.
4. “Qooduu”, Comma (,): is used to separate listing in a sentence or to separate the elements in a series.
5. “Tuqlamee colon”, Colon (:): the function of the colon is to separate and introduce lists, clauses, and quotations, along with several conventional uses, and etc. Unlike English language apostrophe (’) is not punctuation mark in Afaan Oromo, rather it is part of words. For example, har’a (today), re’ee (goat) etc.

6.4. Word Structure

The word, in Afaan Oromo “jecha” is the basic unit of a language. It is also a unit of language that comprises one or more sounds that can stand independently and make sense. According to Anbase, the words of Afaan Oromo may run from very few monosyllabic words to polysyllabic words up to seven syllables. The writing system of the language is straightforward, that means, it is written as it is read and read as it is written.

Afaan Oromo words are also differentiated from one another by white space characters. Hence, the task of taking an input sentence and inserting legitimate word boundaries, called word segmentation (tokenization) for information retrieval purposes, is performed by using the white space characters. The word is the smallest unit of a language. There are different methods for separating words from each other. However, most of the world language including English uses the blank character (space) to show the end of a word. Some long words are been cut in written form (abbreviation), with the symbols "/",".", and therefore this symbol should not determine a word boundary. The usual parenthesis, brackets, quotes, all kinds of marks, are being used to show a word boundary in Afaan Oromo.

6.5. Sentence Structure

Afaan Oromo and English are different in their syntax and sentence structure. Afaan Oromo language uses subject-object-verb (SOV) language because it has a flexible or variable word order Subject-verb-object (SVO) is a sentence structure where the subject comes first, the verb-second and the third object. For instance, in the Afaan Oromo sentence “Fantaan Bashan Dhugee” or Preferably “Inni Bishaan Dhugee” or “Bishaaan Dhugee Fantaan”? “Fantaan “is a subject, “Bishaan” is an object and “Dhugee” is a verb. For that reason, it has an SOV structure. The translation of the sentence in English is “Fanta Drink’s Water” which has an SVO structure because it has a fixed word order. There is also a difference in the formation of adjectives in Afaan Oromo and English. In Afaan Oromo adjectives follow a noun or pronoun; their normal position is close to the noun they modify while in English adjectives usually precede the noun, i.e. Afaan Oromo adjective agree with its head noun, this is not the case in English. For instance, miicaayyoo bareeduu (beautiful girl), bareeduu (adj.) follows miicaayyoo (noun). Afaan Oromo sentence is terminated like English and other languages that follow the Latin writing system. That means, the full stop (.) in statement, the question mark (?) in interrogative and the exclamation mark (!) in command and exclamatory sentences mark the end of a sentence and the comma (,) which separates listing in a sentence and the semicolon is to mark a break that is stronger than a comma but not as final as a full stop balance [14].

7. The Dataset Used

The dataset used in this section is related to Amazon data. We collected several subsets of Amazon product data, but here we tried to collect 5 categories. The features we used from this data include user_id, item_id, cate_id, and times_stamp. Table 1 shows the number of data used. In this section, we show the set of behaviors of user u with (b1; b2;...; bn). Here we intend to examine k behavior of the user and identify the k + 1 behavior of the user, k can be between 1 and n - 1, in other words, we intend to examine n - 1 behavior and predict n behavior.

Table 1. *Statistics of dataset used.*

Dataset	fayyadamoota	maalimaa	Akaakuu	fakkeenya
Electeriikii	192403	63001	801	1689188
uffata	39387	2303	484	278677

8. Competing Methods for Comparison with the Proposed Method

In this section, different methods are presented to be compared to the proposed method. These methods are mostly similar to proposed method but are different in architecture while learning and suggesting. Thus, these methods are as follow:

1. BPR-MF: Bayesian ranking offered by Randall provides a framework for ranking based on business networks. In this solution, user-product pairs are used which, if the user chooses or orders the product, the pair between the user and that product gets the value of true and otherwise the value of false and consequently, after training the network with this method is able to predict based on these pairs.
2. Bi-LSTM: In this method, the past of a user is encoded and he able to evaluate and train users’ past with higher performance and speed. This method was provided by Zhang in 2014.
3. Bi-LSTM+Attention: In this method, through Bi-LSTM, which only deals with the purchase relationship or user search for the product, an extension was added that can take into account the user’s attention so it can provide better recommendations.
4. CNN+Pooling: This method uses the CNN structure, which is able to demonstrate excellent performance using these neural networks. In this method, pooling is also used for encoding in order to reduce the volume of users’ past behaviors and speed up the evaluation process.

9. Results Obtained from Several Types of Behavior

We first calculated the average AUC of the user for all data received from Amazon in the following table 2 shows that. It can be seen that our proposed method is much better than its competitor methods, especially when the user’s behavior is of depth, because the method we mentioned is capable of managing and evaluating users’ deep behaviors.

Table 2. *Average AUC.*

	Electro.	Cloth.
BPR	0.7982	0.7061
Bi-LSTM	0.8757	0.7869
Bi+LSTM+Attention	0.8769	0.7835
CNN+Pooling	0.8804	0.7786
MyAlgorithm	0.8921	0.7905

Table 3. *Calculating the auc on the amazon data.*

	Electeriikii	Uffata
BPR	0.7982	0.7061
Bi-LSTM	0.8757	0.7835
CNN	0.88	0.767

It can also be seen in the chart of table 3 that our proposed method is capable of creating the coverage with a very high speed compared with CNN-based methods on the dataset. This shows high performance and high quality of our proposed method, which is able to have a proper performance on any behavior. we use weighted association rules to discover these patterns to improve the quality of recommendation [13].

10. Conclusion

The proposed method in this article is of a high accuracy in evaluating users’ behaviors and is able to offer very useful suggestions in proportion to user behavior. This evaluation of behaviors is based on neural networks and is able to predict future behaviors of the users by examining the past behaviors of the users, and can therefore provide users with very useful suggestions using the user's future behavior. We looked evaluated various models such as one2one, all2one and all2all, and it was observed that all2one performs much better than the other models, in which different behaviors are trained and a prediction is made for each behavior.

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