Deep Learning Approach for Recommender Engine

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***Abstract*—** for advancement in the fields like speech recognition, natural language processing, audio recognition and Machine translation, the deep learning approach is best suitable approach in recent times. For capturing of non-linear and non-trivial relationship, the best effective approach is deep learning. Further, as compare to other traditional models for recommender engine, the codification is effectively enabled by this method for the complex abstraction at higher layers as data representation. This paper presents comprehensive review on the recommender engine based on deep learning. Furthermore, we focus on the current research work based on recommender engine using the concept of deep learning. Apart from it, this paper also highlights the traditional strategies used for recommender engine.

Keywords: *Deep learning, Recommender Engine, Recommended Engine based on deep learning.*

I. INTRODUCTION

Advancement in the technology leads to the overloading of data, which creates a difficulty for individual to make a right decision [14]. The intensive increase of the data necessitates the emergence of new concept named as recommender system. The main basic point is to get the personalized list for the user by recommending the interested products or items automatically, which is done by analyzing the liking information and user behavior history [4]. In addition, without customer's preference list the recommended engine can even recommend the unfamiliar products of interest to the user. Recommender engine is used by various companies to handle their customers or user in order to increase the sale and to win the heart of customer by recommending best suited products. To cite an example, Amazon has designed their own recommendation system, which is capable of handling around 10 million of users and items in near real system.

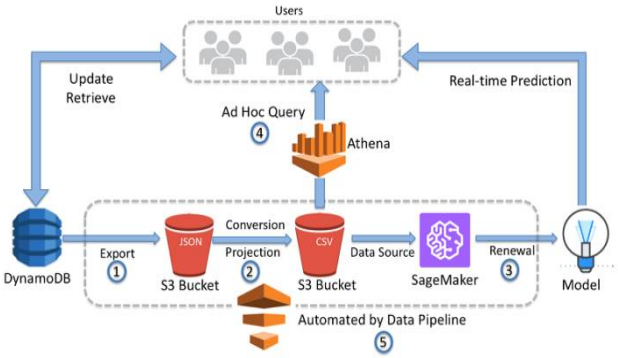

Figure a: Architecture for recommender engine [8]

Figure a, presents the use of Amazon DynamoDB table data in Amazon S3 through the Data pipelines of Amazon web Services. The quoted below are the stages that are followed by data in the architecture:

- The complete content of DynamoDB table is copied by the data pipeline on regular basis into S3 as JSON.
- Further, in order to use JSON files as data source for Amazon Sage Maker, that is converted to CSV (comma separated value) file format.
- Next, updating of endpoint and renewal of Model article is done by Amazon Sage Maker
- With Athena of Amazon, the files become ready for ad hoc inquiries.
- The data pipeline handles this complete flow and repletion of cycle is done based on scheduled maintained by customer's needs.

II. TECHNOLOGIES AND BACKGROUND NOTIONS

This section discusses about the main basic concepts and simple terminologies related to recommended engine along with deep learning concept. The recommended system is portioned into three sort of types as per current study by various researchers [2]:

A. Content-based recommended engine

B. Collaborative filtering based recommended engine

C. Hybrid recommended engine.

A. Content-Based recommended engine:

This engine provides the recommendations to user by making the full use of user's profile and content of product or item viewed by user as shown in Figure b. Firstly, the sufficient amount of user's interested items are analyzed by this method. Secondly, on the basis of this analysis the user profile is recognized. At the end, recommended engine find the database in order to select a proper and best suited items as per user profile [5]. However, it is hard to get the user preference from the content of items viewed by the users. In the field of data mining or machine learning, myriads of approaches are there to resolve such sort of flaws. To exemplify, recommended engine begins with the collections of books that the reader has previously read and do the content analysis of the books obtained.

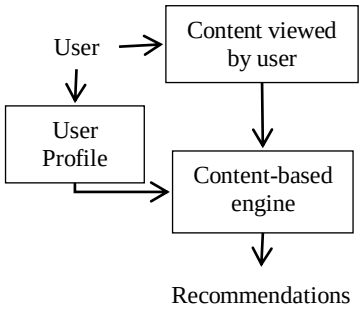

Figure b: Content-based Filtering

Further, with help of text mining strategies, the process key word extraction is performed. Finally, the multiple dimensional vector is used to represent the book after integrating all the keywords by their particular weights. The main another point is that these vectors represents the readers interest, so, in order to get the centers of these vectors the Particular clustering algorithms [13] are implemented.

B. Collaborative filtering recommended engine:

This approach is as if a social filtering as it does the information filtering with help of other people recommendations.CF (collaborative filtering) depends on the rating of any item by other users as shown in Figure c.

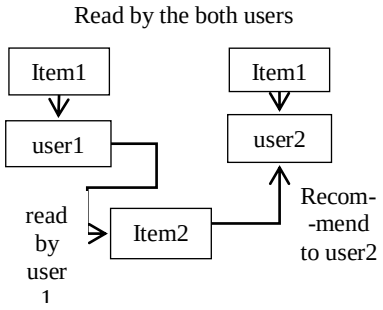

Figure c: CF based RE

This is based on the basic assumption that the similar ratings by the users, most probably possible related preferences. The technique used by CF (collaborative filtering) is statistical technique in order to get the resemblances among the product vector or users. Collaborative filtering mentions product centered on the curiosity of other accordant users or recognize the products related to those beforehand rated by the user which is actually targeted. It uses statistical techniques to find the similarity between the user or item vector. CF (collaborative filtering) methods can be classified into two categories Memory-Based and Model-Based [11].

C. Hybrid recommender systems

This sort of system is designed by the combination of various available recommender engines in order to form a more robust structure as shown in Figure d.

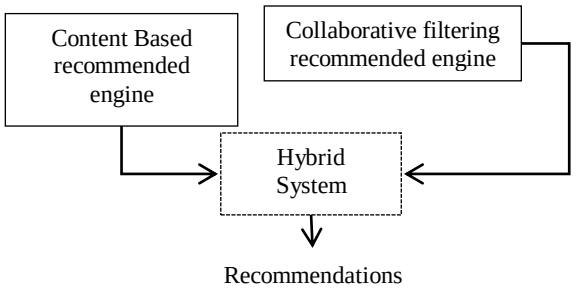

Figure d: Hybrid recommended system

Various recommender engines like CF (collaborative filtering), Content base filtering, contain various types of different strengths and weaknesses, which act as driving force behind the construction of hybrid approach. All recommender engines work effectively at different situations like some work effectively at cold start, however another work effectively in case of availability of sufficient amount of data. In order to develop a system with advanced general robustness, this system tends to hold the complementary powers.

III. DEEP LEARNING APPROACH

This section includes the concept of deep learning embedded with traditional methods. Firstly, we will focus on concept of content-based recommended system using deep learning. Next, we find the detail of deep learning based collaborative filtering recommended engine. Finally, we will introduce the deep learning concept in the context-aware recommended systems.

A. Content–based recommended system using deep learning:

Items and user's information is used to design a content-based recommended system. The supplementary information like images, videos and texts is also taken into consideration. In order to record the non-trivial and non-linear user item correlation, the deep learning concept is used in content-based recommended system. Further, at the higher layers, it enables the codification for the highest complex abstraction as the data abstraction [9]. Moreover, the plentiful reachable data resources like textual and visual information is used to catches the difficult interactions within the data itself.

B. Collaborative-filtering recommended engine using Deep learning:

On the way of solving myriads of problems in the real world, the widely used method is collaborative CF (collaborative filtering). However, as per traditional CF (collaborative filtering), the handling of real life applications degrades performance of recommendations because the rated matrix is normally a kind of sparse matrix.

On the way to solve the sparse data problem, the CF (collaborative filtering) method is improved which utilize the growing quantity of side information. But, due to sparse behavior the latent learned parameters are not effective. In current trend scenario, some researchers make the use of deep learning with Collaborative-based recommended approach to get the significant results of recommendation engines.

i. Collaborative-filtering method- based on Auto encoder:

Collaborative Filtering model based on Autoencoder [12] is the first model for recommendations. It decomposes the partial observed vectors by integer ratings instead of using them as original. Auto encoder-based collaborative filtering recommendation model in which ratings based on users or items in R Rating Matrix are used as input for the model [12]. Further, encoding and decoding process is used to produce the output and reconstruction errors are minimized in order to optimize the parameters of model.

ii. *Collaborative-filtering method – based on Restricted Boltzmann Machine*

RBM is sort of neural net having two layers, which develop the deep-belief network model. First layer is known as layer of visible units or input layer and second one is known as hidden connection layer. This Neural network is efficient enough for solving the complicated learning issues by recognizing the innate essential expression of data. The removal of connection between the similar layers leads to the improvement of learning capacity. In order to fit the implicit feedback information, some researchers proposed the use of conditional Restricted Boltzmann Machine (RBM) [1]. In order to adjust to these restrictions, the score rating is presented only in one hot vector, reason being, the visible layer of this machine is restricted to binary values only.

C. Context aware recommender engine - based on deep learning:

Context aware recommender engine can be implemented using deep learning concept. In Numerous complex recommendation circumstances the deep learning model is meritoriously incorporate the context information into recommender engine along with the fetching of latent info of the context material [10]. Moreover, over, due to this, it can be integrating into all sort of rough circumstances in order to lessen sparsity of data in this Model [7]. In order to effectively model the situation information, the context-aware recommender systems based on deep learning is used and this is act as its current basic application. Various researchers suggested the different sort of approaches or novel model like CA-RNN (context-aware recurrent neural networks). The adaptive context-based input matrices and adaptive context-based transition matrices are used in CA-RNN instead of constant matrix as input and traditional RNN models transition matrix. Such an input matrices used to collect the outside or external situations in the area where the behavior of user is occurred like location, time, Weather etc.

IV. CONCLUSION

The intense rise in the amount of data necessitates the need for smart models and applications in order to store, process and analyze the information intelligently. These challenges act as driving force behind the emergence of deep learning based recommended engines. Deep learning based on suitable tools support the process of information seeking. The recommender model is designed after recognizing the hidden representation of user and items from the enormous records.

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