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Boltzmann Machines Associated Recommender System: A Review

Dheeraj Kumar Sahni* & Dhiraj Khurana†

Abstract

Nowadays, the information on the internet presents explosive growth; similarinformation from the space of information available overwhelms users. Collaborative filtering is one of the alternatives used for solving this problem. Recommendations are the need of daily life to choose the better alternative from the given choices. Everyone uses recommendations to approach the good items and services in this interconnected world. The recommender system is a software solution to make this process easy. This article presents the application of Boltzmann machines in recommendation systems for the last twenty years.

Keywords: Boltzmann Machine (BM), Neural Network, Recommender System

1. Introduction

Boltzmann Machine (BM) is a collection of interconnected neurons that makes the functionality of decisions such as to be on or off (G.E Hinton *et al*., 2007). It was a model of Geoffrey Hinton that learned the internal representation of the input. It gives a new direction to solve two problems, named a search problem and a learning problem (G.E Hinton *et al*., 2007). It is a group of

* Department of Computer Science & Engineering, University Institute of Engineering & Technology(UIET), Maharshi Dayanand University (MDU), Rohtak, Haryana, India; dheeraj.rs.uiet@mdurohtak.ac.in
† Department of Computer Science & Engineering, University Institute of Engineering & Technology(UIET), Maharshi Dayanand University (MDU), Rohtak, Haryana, India; dhirajkhurana@mdurohtak.ac.in

interconnected visible neurons and hidden neurons. Visual neurons and hidden neurons are represented in Fig. 1. The unknown probability distribution based on samples from the distribution can be used as learning input. Learning in the initial model of the BM is much slower than in the present scenario of BM. The unconstrained inter-connection in the neurons limits its use practically (Raza *et al.*, 2022). The learning capability of BM varies with an increase in the increasing number of interconnected neurons. The restricted BM solves the problem of unconstrained inter-connection of neurons (Jawaheer *et al.*, 2010). Limiting the number of neurons helps in the faster training of BM. Also, the learning in the constrained neuron model is achieved by making small changes to the weight and reducing the energy consumption of the model.

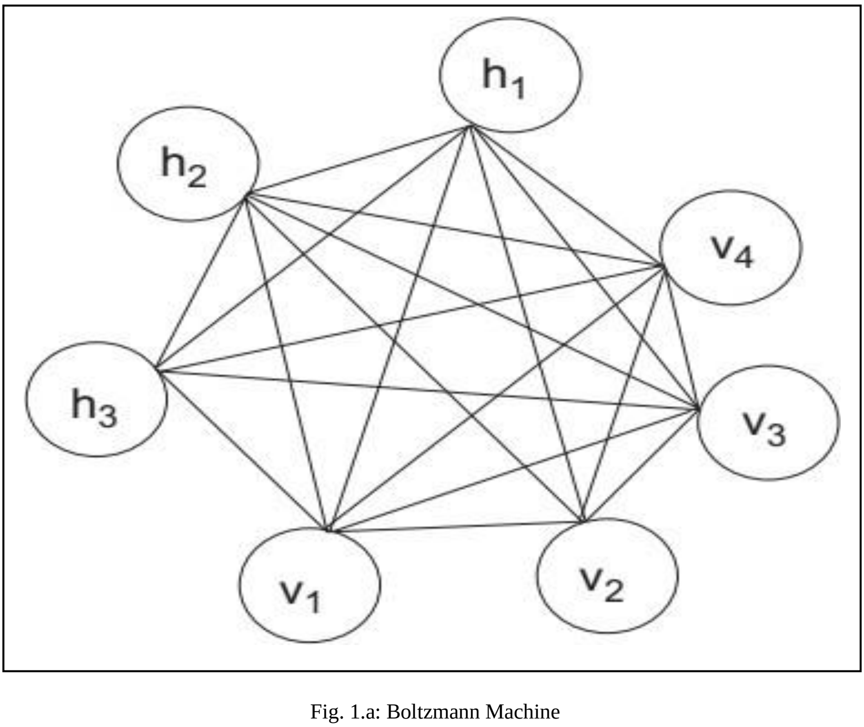

Fig. 1.a: Boltzmann Machine

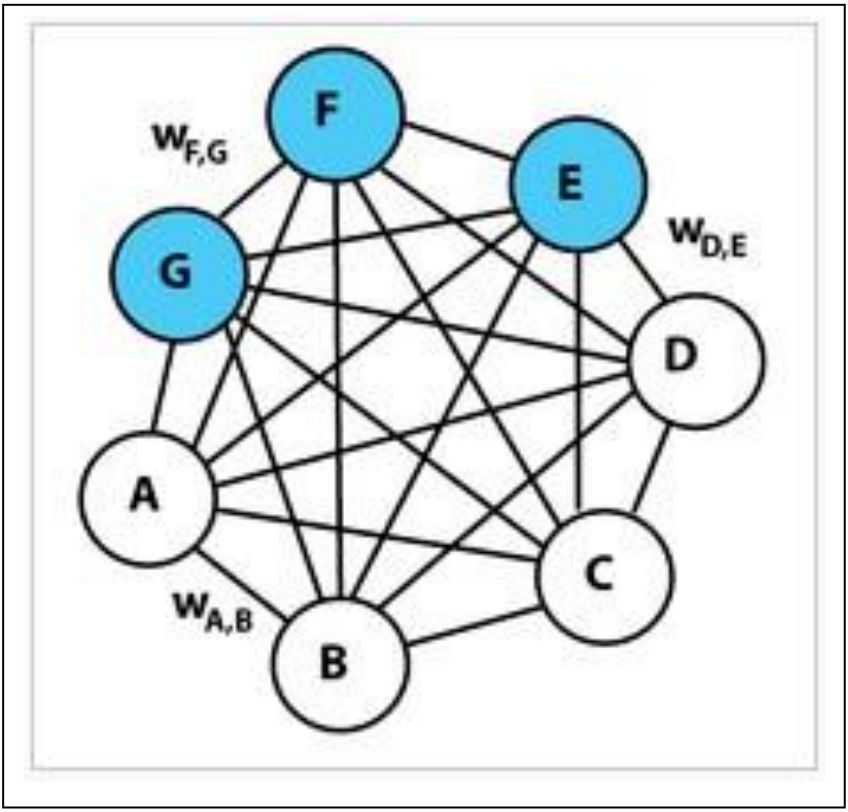

Fig.1b: Boltzmann Machine with Weights

The fig. 1(a), and (b) present the interconnection of constrained neurons in the Boltzmann machine. Here, h1, h2, h3, and v1, v2, v3, and v4 are the nodes of BM which represent the visible neurons in the Boltzmann machine. Fig. 1(b) presents the weights between nodes specified on the edges. The Energy E in BM can be represented by

$$E = \sum_{i<j} W_{i,J}\, S_i S_j + \sum_{i} \theta_i S_i$$

where,

Wi, j = connection strength between nodes i, jSi = state, Si ∈ {0,1}

θ = bias of unit

In the given diagram, the sum of its weight and biases can be calculated as:

$$Zi = bi + \sum_{i,j} Si\, Wi,\ j$$

Unit i transform to unit j with the probability metrics calculated by the logistics equation as follows:

$$\text{prob}(Si = 1) == \frac{1}{1+e^{Zi}}$$

The Boltzmann machine replaces associative memory in neural networks with the limitation of local minima. The restricted BM is one of the solutions to the problem (Nair *et al.*, 2010).

1.1. Types of Boltzmann Machine (BM):

Since the 85s, several researchers have been using the BM in different applications of RS. The basic model with distinct parameters makes BM another machine which is as follows:

Restricted BM with Implicit Feedback (RBIM) (Biswal et al., 2021)
Unsupervised Boltzmann Machine (UBM) (Harshvardhan et al., 2021)
Content Restricted BM (CBM) (Deshmukh et al., 2021)
Conditional Restricted BM (CRBM) (Chen et al., 2020)
Content-boosted RBM (CBRBM) (Liu et al., 2014)
Gaussian-Bernoulli deep BM (GBDBM) (Cho et al., 2013)
Deep BM (DBM) (Salakhutdinov et al., 2012)
Tied Boltzmann Machine (TBM) (Gunawardana et al., 2008)
Restricted Boltzmann Machine (RBM) (Salakhutdinov et al., 2007)
Non-Binary Units BM (NBUBM) (Welling et al., 2005)
Higher Order BM (HOBM) (Sejnowski et al., 1987)
Mean Field BM (MFBM) (Peterson et al., 1987)
Conditional BM (CBM) (Ackley et al., 1985)
Boltzmann Machine (BM) (Hinton et al., 1983)

1.2. Recommender System

Recommender system is a collection of programs to do the recommendation for a specific purpose (Teppan *et al.*, 2008). Based on the availability of input from the user or standard historic data there are various types of recommender systems created using Boltzmann machines such as hybrid RS (Mansur *et al.*, 2022), content base RS, deep learning associated RS etc. Recommendation systems are ubiquitous, where BM makes the scope wider (Hinton *et al.*, 2012). In the coming section Fig. 2

present a proposed recommendation model with BM to understand the working better.

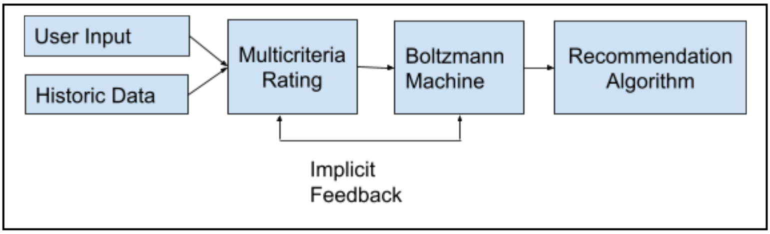

Fig. 2 Recommender System Using BM

1.3. Mind Map of Boltzmann Machine

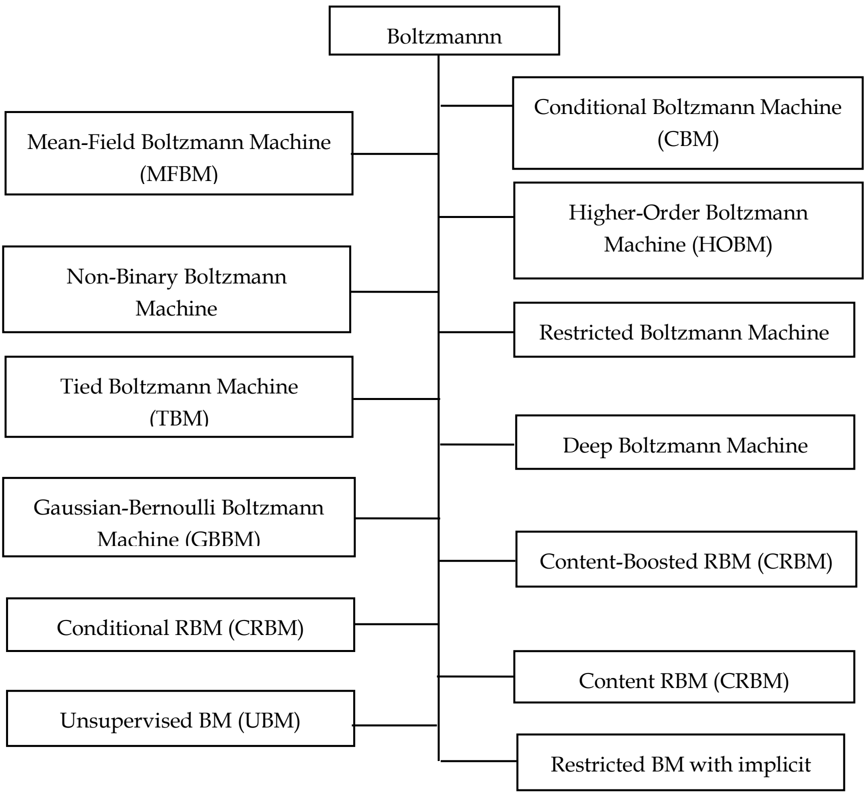

Fig. 3 Mind Map of BM

2. Literature

In this, systematic literature is presented from the 83s to the present scenario of the Boltzmann machine. Initially, the BM was used as a group of neurons connected to interpret some input data on the nodes and assign the corresponding probability and inferred values like true and false to the internal objective function (Hinton et al., 1983). With the advancement in deep learning and artificial intelligence, several changes have been made in the initial version of BM. (Ackley et al., 1985) presents some examples to apply learning algorithms to internal representation to modify the existing structure. A deterministic mean-field is a solution propounded by (Peterson et al., 1987) to replace the stochastic measurement. Third-order BM improves the cubic energy of stochastic neurons and base for higher order BM suggested by (Sejnowski et al., 1987). The Boltzmann machine plays a vital role in the recommender system (Behera et al., 2021) presents a hybrid model of the recommender system using RBM, one of the solutions to the cold start problem using TBM (Gunawardana et al., 2008), handling large data sets in collaboration of RBM with collaborative filtering (Salakhutdinov et al., 2007). Boltzmann machines have wider applications in music, and video recommendations suggested by (Hazrati et al., 2021), also address the issues while recommending the videos to the unknown user and propose a solution using visual features of RBM. Boltzmann machines are getting popular with the growth of deep neural networks; several researchers have been working on integrating the deep learning features with collaborative filtering and content-based filtering, using variants of BM (Negi et al., 2021). Implicit feedback is a novel feature (Biswal et al., 2021); while recommending music to some users, the number of times a song is listened to by the known user is the implicit feedback for the system. (Deshmukh et al., 2021) proposed the system to recommend diet plans to the thyroid patient and expert, evaluate the results using content - RBM, the outcome shows an improvement in the patient for the given data set. In the world of visual media and internet information systems, the RBM is used with a variety of applications to solve complex tasks such as feature extraction, neuro-imaging, radar-target recognition, etc. the unsupervised BM based time aware RS shows a good response in the context of movie rating data sets (Harshvardhan et al., 2021).

Conditional constraint RBM with real-time data sets created by (Chen *et al.*, 2020) model the user rating behavior with top- k recommendation, the overall progress achieves good accuracy in comparison with related work. (Kuo *et al.*, 2020) focus on the hybrid model with mathematical differential evolution. The mixture model is a combination of cluster-based RBM and collaborative filtering with several optimization algorithms to update RBM parameters. With the explosive growth of information on the internet, thetask of recommendation becomes complex because handling large items with their features is tough to manage in a single place. Collaborative filtering with the limitationof cold start problems is still in its infancy (Polonioli *et al.,* 2021). The mixture of auto-encoder-based collaborative filtering models is a solution to achieve fast recommendations with large data sets, but the big data sets still limit the system performance (Wang *et al.,* 2019). Sparsity is one limitation of the recommender system, which is still unsolvable (Idrissi *et al.,* 2019). still, to some extent, RBM alleviates this issue. Recommendations are followed from the last decade, based on the basic components such as user ratings, item metadata (MD), and user demographic (UD). The integration of MD, UD with RBM-based collaborative filtering significantly improves the accuracy of recommendation (Verma *et al.,* 2018). Is RBM equivalent to a tensor network? Is a question published several time in a different article, one of the answers replied to publisher by (Chen *et al.,* 2018) building a bridge between RBM and tensor network states. Tensor network is an array of multi-dimension used to store user information like 2-D, 3-D, tensor are the most popular example of the scenario. Recommendations are chains that expand from one user to another based on the user information, such as ratings created by the user in the past (either explicit or implicit); however, these ratings are fond sparse (Wang *et al.*, 2018). Hence, the prediction based on a sparse data set cannot be suitable for the users. The grouping of user/items into clusters is one alternative to solve this issue while several algorithms are available to distribute user's/items' into groups. Fuzzy- C means clustering with the combination of RBM is an attempt to predict user preferences on the Movie Lens data set (Behera *et al.*,2018). Another solution to solve the problem of data sparsity is to fill the missing entries of rating in the matrix and can be replaced by item category; tested on movie lens data set makes an improvement in comparison with traditional RBM and singular value decomposition system (He *et al.*, 2017). There are some similarities between the BM and Monte-Carlo cluster algorithms, such that the MC -cluster obtains repeated random sampling of stochastic (Danilova *et al.*, 2022). At the same time, BM is the stochastic probability distribution mechanism among the neurons (Wang *et al.*, 2017). The nearest trusted relationship is propounded by the (He *et al.*, 2016), shows more accurate predictions without converting the users' rating in k - dimensional units, and real-valued CRBM is used as the novel model to present the outcome *(*Pramod *et al., 2022)*. Further, extending the sparsity problem, item aware category on the small data set tested by (Liu *et al.*, 2015) (Y. Hu *et al.,* 2008) integrated with RBM. One of the solutions to replace the missing entries in the user rating matrix to overcome the data sparsity suggested (Liu *et al.,* 2014) can be a Naive Bayes classifier and then apply the updated user demographic and item category information to RBM on denser rating matrix (Abbas *et al.,* 2022). "More the sparsity less the accurate recommendation" a phrase shows the significance of the Netflix challenge (Feuerverger *et al.,* 2012) such thata data set with 99% sparsity has a great impact on the recommender system. Linear arrangement (blending), a set of collaborative filtering algorithms, increases the accuracy in such cases where the removal of sparsity is a big challenge (Parra *et al.,* 2011), (Jahrer *et al.*, 2010). Unified BM makes a hybrid model which combines the feature of content-based, collaborative filtering with probabilistic BM to overcome the limitation of CF, and CB and perform experiments on movie and shopping data sets (Gunawardana *et al.*, 2009, (Aditya *et al.*, 2017).

3. Discussion

In the earlier section, we have studied variants of Boltzmann machines regarding the recommender system with its limitations and application. Nowadays, RS is the backbone of the e-commerce system (Roy *et al.*, 2022), and the RS players are still facing issues with changing the needs of users and the environment (Asemi *et al.*, 2022). The traditional issues like cold start problem, sparsity, and accuracy are still in their infancy (Batmaz *et al.,* 2019). Novel techniques such as BM, and deep learning gives a better solution to the limitations of RS (D. *et al.*, 2022). The significant challenges of players of RS are still unsolvable (Lee *et al.*, 2021). Training of models (Jiang *et al.*, 2023), learning criteria such as supervised learning, unsupervised learning are subject of future research for newbies in the boltzmann machine associated recommender system (Georgiev *et al.*, 2013). Ethical and psychological perspectives are still in their initial state (Adomavicius *et al.*, 2005).

4. Conclusion

The whole study focuses on the hybrid model functionality of recommender system, Boltzmann machine and its application in respective domains. The observations, analysis presents the improved accuracy and sparsity in recommendation with large data sets. The issues like cold start problem, training of models is solved to some extentusing deep learning enabled Boltzmann machines.

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