

# A Hybrid Recommendation Engine Based On Boltzmann Machine and Auto Encoders

Satheesh Kumar D<sup>1</sup>, Magesh D<sup>2</sup>, Dhiyanesh B<sup>3</sup>, Bhuvanesh S<sup>4</sup>

<sup>1,2,3,4</sup> Assistant Professor, Department of Computer Science and Engineering,  
Hindusthan College of Engineering and Technology, Coimbatore, India

## Abstract

In current years, the quantity of information gift on line has grown exponentially. A principal part of this information is associated with internet-primarily based totally e-trade platforms. The assessment of such information and/or the extraction of statistics is hard because of its massive quantity. Recommender Systems (RS) gift an automatic and green approach to this problem. Recommender structures examine the consumer profile/conduct and gives merchandise relative to the consumer's interests. RS perhaps primarily based totally on collaborative filtering, content-primarily based totally, of those strategies. Online advice via Hybrid Recommendation System performs a crucial function in e-trade and is appeared as one of the nice strategies for making viable pointers for customers. This studies analyses the advice structures primarily based totally on Boltzmann device and Auto Encoders. Two strategies implemented in advice System primarily based totally on Hybrid advice are item-primarily based totally and consumer-primarily based totally approaches. Recommendation Systems (RS), use a form of statistics filtering era that mines historic consumer conduct to excavate statistics and discover the person desires of customers in today's surroundings of statistics overload. Thus far, researchers have proposed quite a few advice strategies which have been efficaciously implemented to numerous fields, e.g., pointers concerning Amazon buying music, and the news. Existing advice algorithms specifically consist of content-primarily based totally pointers and collaborative filtering and knowledge-based pointers. Of these, Hybrid method has attracted the eye of researchers in each academia and enterprise because of its excessive accuracy and extensive variety of pointers.

**Keywords:** Recommender Systems, Boltzmann Machine, Auto encoder

## 1. INTRODUCTION

A Recommender machine, or a advice machine (occasionally replacing 'machine' with a synonym which includes platform or

engine), is a subclass of data filtering machine that seeks to are expecting the "rating" or "preference" a consumer might deliver to an object. They are in general utilized in business applications.

Recommender structures are applied in quite a few regions and are maximum generally diagnosed as playlist mills for video and tune offerings like Netflix, YouTube and Spotify, product recommenders for offerings which includes Amazon, or content material recommenders for social media structures which includes Facebook and Twitter. These structures can function the usage of a unmarried input, like tune, or more than one inputs inside and throughout structures like news, books, and seek queries. There also are famous recommender structures for particular subjects like eating places and on line dating. Recommender structures have additionally been evolved to discover studies articles and experts, collaborators, and economic offerings. Recommender structures generally employ both or each collaborative filtering [1] and content material-primarily based totally filtering (additionally called the personality-primarily based totally approach), in addition to different structures which includes knowledge-primarily based totally structures. Collaborative filtering tactics construct a version from a consumer beyond behavior (gadgets formerly bought or decided on and/or numerical rankings given to the ones gadgets) in addition to comparable selections made with the aid of using different users. This version is then used to are expecting gadgets (or rankings for gadgets) that the consumer might also additionally have a hobby in. Content-primarily based totally filtering tactics make use of a chain of discrete, pre-tagged traits of an object so that it will advocate extra gadgets with comparable properties. Current recommender structures generally integrate one or extra tactics right into a hybrid machine. The variations among collaborative and content material-primarily based totally filtering may be validated with the aid of using evaluating early tune recommender structures – Last.fm and Pandora Radio.

## 1.1 OBJECTIVE

A Recommender System refers to a gadget this is able to predicting the destiny desire of a fixed of objects for a person, and propose the pinnacle objects. One key cause why we want a recommender gadget in present day society is that humans have an excessive amount of alternatives to apply from because of the superiority of Internet. In the past, humans used to save in a bodily shop, wherein the objects to be had are limited. For instance, the range of films that may be located in a Blockbuster shop relies upon on the scale of that shop. By contrast, nowadays, the Internet permits humans to get entry to considerable sources on-line. Netflix, for example, has a substantial series of films. Although the quantity of to be had statistics increased, a brand new hassle arose as humans had a difficult time choosing the objects they really need to see. This is in which the recommender gadget comes in. This article will come up with a quick advent to 2 normal approaches for constructing a recommender gadget, Collaborative Filtering and Singular Value Decomposition. An advice gadget is a pc application that enables a person find out merchandise and content material with the aid of using predicting the person's score of every object and displaying them the objects that they might fee highly. Recommendation structures are everywhere. If you've ever searched for books on Amazon or browsed thru posts on Facebook, you've used the advice gadget without even understanding it. With on-line shopping, customers have almost endless choices. No one has sufficient time to strive each product for sale. Recommendation structures play a critical function in assisting customers discover merchandise and content material they care approximately. Recommendation structures have numerous one of a kind makes use of. The maximum not unusual place use for an advice gadget is rating merchandise with the aid of using how a whole lot a person would really like them. If a person is surfing or trying to find merchandise, we need to expose them the goods they would really like maximum first with inside the list. Recommendation structures also can be used to discover how comparable one of a kind merchandise are to every different. If merchandise is very just like every different, they may enchantment to the equal customers.

Product similarity is mainly beneficial in instances in which we don't understand a whole lot approximately a specific person yet. We can propose comparable merchandise, even though the person hasn't entered any in their personal product critiques yet. We also can use advice structures to determine out if one of a kind customers are just like every different. If customers have comparable alternatives for merchandise, we will anticipate they've comparable interests. For example, a social community can use this statistic to signify the 2 customers need to emerge as pals. Recommendation structures in motion on e-trade web sites. When you purchase something on Amazon, the following time

you go to you'll see endorsed merchandise primarily based totally for your purchase. This is powered with the aid of using a advice gadget. But that's simply the top of the iceberg. Social media web sites like Facebook and Instagram depend closely on advice structures. These web sites use advice structures to determine which submit to show for your timeline and which new pals to propose to you. Netflix makes use of a advice gadget to determine which films and television suggests to give to you. They are well-known for his or her studies and advice structures. In 2006 they began out the Netflix prize which become a competition for the primary crew which can enhance the advice accuracy with the aid of using 10% might win a million dollars. Three years later the task become finished and the prize become awarded. Recommendation structures additionally pop up in all forms of different merchandise. Online relationship programs use advice structures to determine which customers to expose to every different. Banks and funding groups use advice structures to suit one of a kind debts and offerings to customers. Insurance groups do the equal.

## 1.2 APPROACHES

### 1.2.1 Collaborative filtering:

One approach to the look of recommender systems that has wide use is cooperative filtering [1]. cooperative filtering is predicated on the belief that individuals World Health Organization in agreement within the past can agree within the future, which they're going to like similar varieties of things as they likeable within the past. The system generates recommendations victimization solely data concerning rating profiles for various users or things. By locating peer users/items with a rating history like the present user or item, they generate recommendations victimization this neighborhood. Collaborative filtering ways are classified as memory-based and model-based. a widely known example of memory-based approaches is that the user-based formula whereas that of model-based approaches is that the Kernel-Mapping Recommender. A key advantage of the cooperative filtering approach is that it doesn't suppose machine complex content and thus it's capable of accurately recommending advanced things like movies while not requiring associate "understanding" of the item itself. several algorithms are utilized in mensuration user similarity or item similarity in recommender systems. as an example, the k-nearest neighbor (k-NN) approach and therefore the Pearson Correlation as initial enforced by Allen. When building a model from a user's behavior, a distinction is commonly created between specific and implicit varieties of knowledge assortment. Examples of specific knowledge assortment embrace the following:

- Asking a user to rate associate item on a wage scale.

- Asking a user to go looking.
- Asking a user to rank a set of things from favorite to least favorite.
- Presenting 2 things to a user and asking him/her to settle on the higher one amongst them.
- Asking a user to form a listing of things that he/she likes (see Rocchio classification or different similar techniques). Examples of implicit knowledge assortment embrace the following:
  - Observing the things that a user views in a web store.
  - Analyzing item/user viewing times.
  - Keeping a record of the things that a user purchases on-line.
  - Obtaining a listing of things that a user has listened to or watched on his/her pc.
  - Analyzing the user's social network and discovering similar likes and dislikes. Collaborative filtering approaches typically suffer from 3 problems: cold begin, measurability, and scantiness.
  - Cold start: For a replacement user or item, there is not enough knowledge to create correct recommendations.
  - Scalability: In several of the environments within which these systems build recommendations, there are scores of users and product. Thus, an oversized quantity of computation power is commonly necessary to calculate recommendations.
  - Sparsity: the amount of things sold-out on major e-commerce sites is very massive. the foremost active users can solely have rated a little set of the general information.

Thus, even the foremost widespread things have only a few ratings. One of the foremost renowned samples of cooperative filtering is item-to-item cooperative filtering (people World Health Organization purchase  $x$  conjointly purchase  $y$ ), associate formula popularized by Amazon.com's recommender system. several social networks originally used cooperative filtering to suggest new friends, groups, and different social connections by examining the network of connections between a user and their friends. cooperative filtering remains used as a part of hybrid systems.

### 1.2.2 Content-based filtering:

Another common approach once planning recommender systems is content-based filtering [3]. Content-based filtering ways area unit supported an outline of the item and a profile of the user's preferences. These ways area unit best suited to things

wherever there's well-known information on Associate in Nursing item (name, location, description, etc.), however not on the user. Content-based recommenders treat recommendation as a user-specific classification drawback and learn a classifier for the user's likes and dislikes supported product options. In this system, keywords area unit accustomed describe the things and a user profile is constructed to point the sort of item this user likes. In alternative words, these algorithms attempt to advocate things that area unit the same as those who a user likable within the past, or is examining within the gift. It doesn't admit a user sign-in mechanism to come up with this typically temporary profile. especially, numerous candidate things area unit compared with things antecedently rated by the user and also the best-matching things area unit counseled. This approach has its roots in data retrieval and knowledge filtering analysis. To create a user profile, the system largely focuses on 2 styles of information:

1. A model of the user's preference.
2. A history of the user's interaction with the recommender system.

Basically, these ways use Associate in Nursing item profile (i.e., a collection of separate attributes and features) characterizing the item at intervals the system. To abstract the options of the things within the system, Associate in Nursing item presentation formula is applied. A wide used formula is that the tf-idf illustration (also known as vector house representation). The system creates a content-based profile of users supported a weighted vector of item options. The weights denote the importance of every feature to the user and may be computed from on an individual basis rated content vectors employing a kind of techniques. straightforward approaches use the typical values of the rated item vector whereas alternative refined ways use machine learning techniques like theorem Classifiers, cluster analysis, call trees, and artificial neural networks so as to estimate the likelihood that the user goes to love the item. A key issue with content-based filtering is whether or not the system is in a position to be told user preferences from users' actions concerning one content supply and use them across alternative content varieties. once the system is proscribed to recommending content of an equivalent sort because the user is already mistreatment, the worth from the advice system is considerably but once alternative content

varieties from alternative services will be counseled. for instance, recommending news articles supported browsing of stories is helpful, however would be way more helpful once music, videos, products, discussions etc. from totally different services will be counseled supported news browsing. to beat this, most content-based recommender systems currently use some sort of hybrid system. Content primarily based recommender systems may embrace opinion-based recommender systems. In some cases, user's area unit allowed to depart text review or feedback on the things. These user-generated texts area unit implicit information for the recommender system as a result of they're probably wealthy resource of each feature/aspects of the item, and users' evaluation/sentiment to the item. options extracted from the user-generated reviews area unit improved meta-data of things, as a result of as they conjointly replicate aspects of the item like meta-data, extracted options area unit wide involved by the users. Sentiments extracted from the reviews will be seen as users' rating scores on the corresponding options. standard approaches of opinion-based recommender system utilize numerous techniques as well as text mining, data retrieval, sentiment analysis (see conjointly Multimodal sentiment analysis) and deep learning.

### 1.2.3 Hybrid Recommender systems:

Most recommender systems currently use a hybrid approach, combining cooperative filtering, content-based filtering, and different approaches. There's no reason why many completely different techniques of identical kind couldn't be hybridized. Hybrid approaches may be enforced in many ways: by creating content-based and cooperative-based predictions singly so combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model studies that by trial and error compare the performance of the hybrid with the pure collaborative and content-based strategies and incontestable that the hybrid strategies will offer a lot of correct recommendations than pure approaches. These strategies may also be wont to overcome a number of the common issues in recommender systems like cold begin and therefore the sparseness drawback, similarly because the data engineering bottleneck in knowledge-based approaches. Netflix could be a

model of the utilization of Hybrid recommender systems [4]. the web site makes recommendations by examination the look and looking out habits of comparable users (i.e., cooperative filtering) similarly as by providing movies that share characteristics with films that a user has rated extremely (content-based filtering). Some mating techniques include:

- **Weighted:** Combining the score of various recommendation elements numerically.
- **Switching:** selecting among recommendation elements and applying the chosen one.
- **Mixed:** Recommendations from completely different recommenders are given along to grant the advice.
- **Feature Combination:** options derived from completely different data sources ar combined along and given to one recommendation rule.
- **Feature Augmentation:** Computing a feature or set of options, that is then a part of the input to succeeding technique.
- **Cascade:** Recommenders ar given strict priority, with the lower priority ones breaking ties within the marking of the upper ones.
- **Meta-level:** One recommendation technique is applied and produces some kind of model, that is then the input employed by succeeding technique.

## 2. PROBLEM DEFINITION

The effectiveness of advice approaches is then measured supported however well a recommendation approach will predict the users' ratings within the dataset. whereas a rating is a precise expression of whether or not a user likable a picture, such info isn't on the market altogether domains. as an example, within the domain of citation recommender systems, users generally don't rate a citation or suggested article. In such cases, offline evaluations could use implicit measures of effectiveness. as an example, it's going to be assumed that a advocate system is effective that's able to recommend as several articles as potential that are contained during a analysis article's reference list. However, this sort of offline evaluations is seen vital by several researchers. as an example, it's been shown that results of offline evaluations have low correlation with results from user studies or A/B tests. A knowledge set standard for offline analysis has been shown to contain duplicate data and therefore to steer to wrong conclusions within the analysis of algorithms. Often, results of questionable offline evaluations don't correlate with truly assessed user-satisfaction. this can be in all probability as a result of offline coaching is extremely



biased toward the highly approachable things, and offline testing knowledge is very influenced by the outputs of the net recommendation module. Researchers have over that the results of offline evaluations ought to be viewed critically.

### 3. EXISTING SYSTEM

Recommender systems sometimes create use of either or each cooperative filtering and content-based filtering (also called the personality-based approach), additionally as alternative systems like knowledge-based systems. cooperative filtering approaches build a model from a user's past behavior (items antecedently purchased or elect and/or numerical ratings given to those items) additionally as similar selections created by alternative users. This model is then accustomed predict things (or ratings for items) that the user might have Associate in Nursing interest in. Content-based filtering approaches utilize a series of separate, pre-tagged characteristics of Associate in Nursing item so as to advocate further things with similar properties. Current recommender systems usually mix one or a lot of approaches into a hybrid system.

#### 3.1 DISADVANTAGE

- The existing system severally implements the 2 approaches of data filtering.
- The cooperative filtering recommends the connected merchandise supported the pre-search history of the users.
- The Content primarily based filtering recommends solely the properties of the search product.
- Recommends the shoppers with obtainable tags.
- Do not render the reliable customization to the shoppers.
- All recommending genus Apis works inside the designed platform.
- Both the system faces the cold begin downside.
- No availableness of coinciding information to advocate the connected merchandise.
- The genus Apis couldn't adapt to dynamical pattern of the customer's style on merchandise.
- The filtration done isn't relevant to the user's time period desires.

### 4. PROPOSED SYSTEM

Most recommender systems currently use a hybrid approach, combining cooperative filtering, content-based filtering, and different approaches. there's no reason why many completely different techniques of constant kind couldn't be hybridized.

Hybrid approaches will be enforced in many ways: by creating content-based and collaborative-based predictions individually and so combining them; by adding content-based capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model (see for an entire review of recommender systems). many studies that by trial and error compare the performance of the hybrid with the pure cooperative and content-based strategies and incontestable that the hybrid strategies will offer additional correct recommendations than pure approaches. These strategies can even be wont to overcome a number of the common issues in recommender systems like cold begin and therefore the sparseness drawback, yet because the data engineering bottleneck in knowledge-based approaches.

#### 4.1 ADVANTAGE

- Recommending customers the foremost relevant merchandise supported their distinctive behaviours.
- Highly filtered merchandise is counseled to the shoppers.
- Personalization takes this into consideration for generating recommendations.
- Recommendation works with the rule based mostly approach towards the information.
- Implementation of hybrid engine to the system that collaborates the information.
- This engine works with the information collaboration of varied algorithms.
- Provides reliable customization to the users.

#### 4.2 USER LOGS:

In laptop security, work in (or work on, signing in, or linguistic communication on) is that the method by that a personal gains access to a system by distinctive and authenticating themselves. The user credentials are usually some type of "username" and an identical "password", and these credentials themselves are typically stated as a login (or a logon or a sign-in or a sign-on). In follow, fashionable secure systems typically need a second issue like email or SMS confirmation for additional security. When access isn't any longer required, the user will sign off (log off, sign out or sign off).

#### 4.3 IMPLEMENTATION OF BOLTZMANN MACHINE

Boltzmann machines (BMs) are introduced as bidirectional connected networks of random process units, which may be taken as neural net- work models. A BM may be accustomed

learn necessary aspects of AN unknown likelihood distribution supported samples from this distribution. In general, this learning method is difficult and long. However, the training downside may be imposing restrictions on the topology, that leads U.S.A. to restricted Ludwig Boltzmann machines (RBMs), the subject of this tutorial. A (restricted) BM may be a parameterized generative model representing a probability distribution. Given some observations, the coaching knowledge, learning a BM suggests that adjusting the BM parameters such the likelihood distribution represented by the BM fits the coaching knowledge furthermore as attainable. Ludwig Boltzmann machines accommodates 2 kinds of units, thus referred to as visible and hidden neurons, which may be thought of as being organized in 2 layers. The visible units represent the first layer and correspond to the elements of an observation (e.g., one visible unit for every pixel of a digital input image). The hidden units model dependencies between the elements of observations (e.g., dependencies between pixels in images). they'll be viewed as non-linear feature detectors. Ludwig Boltzmann machines may also be considered specific graphical models, a lot of exactly aimless graphical models conjointly called mathematician random fields. The embedding of BMs into the framework of probabilistic graphical models provides immediate access to a wealth of theoretical results and well-developed algorithms. Therefore, our tutorial introduces RBMs from this attitude. Com- putting the chance of AN aimless model or its gradient for logical thinking is generally computationally intensive, and this conjointly holds for RBMs. Thus, sampling based mostly ways ar used to approximate the chance and its gradient. Sampling from AN aimless graphical model is generally not simple, except for RBMs Markoff chain Monte Carlo (MCMC) ways ar simply applicable within the sort of Gibbs sampling, which is able to be introduced during this tutorial beside basic idea of Markoff chain theory. when winning learning, AN RBM provides a closed-form illustration of the distribution underlying the observations. It may be accustomed compare the possibilities of (unseen) observations and to sample from the learnt distribution (e.g., to come up with image textures, especially from marginal distributions of interest. for instance, we will we will visible units reminiscent of a partial observation and sample the remaining visible units for finishing the observation (e.g., to resolve a picture in painting task). Boltzmann machines are projected within the Nineteen Eighties. Compared to the days once they once they introduced, RBMs will currently be applied to a lot of attention-grabbing issues because of the rise in procedure power and also the development of latest learning strategies. Restricted Ludwig Boltzmann machines have received plenty of attention recently when being projected as building blocks of multi-layer learning architectures referred to as deep belief networks (DBNs). the concept is that the hidden neurons extract relevant options from the observations. These options will function input to a different

RBM. By stacking RBMs during this approach, one will learn options from options within the hope of inbound at a high level illustration.

#### 4.5 IMPLEMENTATION OF AUTO ENCODERS

An auto encoder could be a form of artificial neural network accustomed learn economical knowledge coding in Associate in Nursing unattended manner. [1] The aim of Associate in Nursing auto encoder is to be told an illustration (encoding) for a group of knowledge, generally for spatiality reduction, by coaching the network to ignore signal "noise". along the reduction side, a reconstructing aspect is learnt, wherever the auto encoder tries to come up with from the reduced cryptography a illustration as shut as potential to its original input, therefore its name. many variants exist to the fundamental model, with the aim of forcing the learned representations of the input to assume helpful properties. Examples area unit the regularized auto encoders (Sparse, Denoising and Contractive auto encoders), well-ried effective in learning representations for resulting classification tasks, and variation auto encoders, with their recent applications as generative models. Auto encoders area unit effectively used for finding several applied issues, from face recognition [5] to feat the linguistics that means of words. Associate in Nursing auto encoder could be a neural network that learns to repeat its input to its output. it's an enclosed (hidden) layer that describes a code accustomed represent the input, Associate in Nursing it's entrenched by 2 main parts: an encoder that maps the input into the code, and a decoder that maps the code to a reconstruction of the first input. Performing the repetition task utterly would merely duplicate the signal, and this can be why auto encoders typically area unit restricted in ways in which force them to reconstruct the input roughly, conserving solely the foremost relevant aspects of the info within the copy. The idea of auto encoders has been widespread within the field of neural networks for many years, and also the initial applications originate to the '80s. Their most ancient application was spatiality reduction or feature learning, however a lot of recently the auto encoder thought has become a lot of wide used for learning generative models of knowledge. a number of the foremost powerful AIs within the 2010s concerned distributed auto encoders stacked within deep neural networks.

#### 4.4 IMPLEMENTATION OF HYBRID ENGINE

Most recommender systems currently use a hybrid approach, combining cooperative filtering, content-based filtering, and alternative approaches. there's no reason why many completely different techniques of constant sort couldn't be hybridized. Hybrid approaches will be enforced in many ways: by creating content-based and collaborative-based predictions on an individual basis then combining them; by adding content-based

capabilities to a collaborative-based approach (and vice versa); or by unifying the approaches into one model (see for a whole review of recommender systems). many studies that by trial and error compare the performance of the hybrid with the pure cooperative and content-based strategies and incontestable that the hybrid strategies will offer additional correct recommendations than pure approaches. These strategies also can be wont to overcome a number of the common issues in recommender systems like cold begin and therefore the spareness drawback, also because the data engineering bottleneck in knowledge-based approaches. Netflix could be an example of the employment of hybrid recommender systems. the web site makes recommendations by scrutiny the look and looking habits of comparable users (i.e., cooperative filtering) also as by giving movies that share characteristics with films that a user has rated extremely (content-based filtering).

## 5. CONCLUSION AND FUTURE

Hybrid Recommendation System performs a crucial function in e-trade and is appeared as one of the nice strategies for making viable pointers for customers. It combining cooperative filtering, content-based filtering, and alternative approaches. Boltzmann machines which may be taken as neural network models with bidirectional connected networks are used to provide recommendation effectively.

The future of the advice systems lies with the collaboration of the data's and therefore the implementation of the co-operative recommendation numerous applications.

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#### AUTHORS

**First Author** – Mr. Satheesh Kumar D, M.E., (Ph.D), Assistant Professor, Department of CSE, Hindusthan College of Engineering and Technology, [dsatheeshme@gmail.com](mailto:dsatheeshme@gmail.com)

**Second Author** – Mr. Magesh D, M.E., Assistant Professor, Department of CSE, Hindusthan College of Engineering and Technology, [maksmeon@gmail.com](mailto:maksmeon@gmail.com)

**Third Author** – Dr. Dhiyanesh B, M.Tech., Ph.D., Assistant Professor, Department of CSE, Hindusthan College of Engineering and Technology, [dhiyanu87@gmail.com](mailto:dhiyanu87@gmail.com)

**Fourth Author** – Mr. Bhuvanesh S, M.E., MBA., Assistant Professor, Department of CSE, Hindusthan College of Engineering and Technology, [sbhuvi16@gmail.com](mailto:sbhuvi16@gmail.com)