Using Self-Organizing Maps for Recommender Systems

Niharika Purbey, Khyati Pawde, Shreya Gangan, Ruhina Karani

Abstract— In this paper, we present an approach called Self-Organizing Map and its application in recommendation systems. Self-Organizing map is a popular unsupervised artificial neural network algorithm. We discuss the SOM algorithm in detail and evaluate its performance. The SOM technique has various advantages over general mining algorithms and hence we choose to discuss this technique. Traditionally, with recommendation systems, collaborative filtering or hybrid systems are used. However, if these techniques are used with artificial neural networks like SOM, the system becomes more efficient.

Index Terms— Self-Organizing Map (SOM), Recommender Systems, Neural Network, Feature Map, Unsupervised Learning.

I. INTRODUCTION

Self-Organizing maps are an unsupervised learning algorithm which is used to visualize high dimensional data sets. This model was first described by Professor Teuvo Kohonen and hence is also called as Kohonen map. Unsupervised learning is a technique of finding a structure in unlabeled data. In other words, it studies how the system can learn to delineate an input pattern with no explicit target outputs. Self-organizing map is a popular technique used for recommender systems. A recommender system aims at making personalized recommendations or suggestions using various knowledge discovery algorithms. Hence, self-organizing map can be used for the purpose of knowledge discovery in recommendation systems. While self-organizing map is similar to the technique of clustering, it has many advantages over general clustering algorithms. In case of a recommendation system, the self-organizing map would organize the model vectors in such a manner that nearby map units represent similar data and distant map units represent different data. Hence, we can make recommendations with this information. In this paper, we discuss the entire process of self- organizing map and its application in recommendation systems. Section 2 of the paper introduces the Self-organizing map algorithm and its working. In section 3, the different properties possessed by this technique are discussed and section 4 briefly gives an evaluation of the system. Section 5, provides the application of SOM in recommendation systems. In Section 6, we provide an example of a music recommendation system which used SOM. Finally, Section 7 presents our conclusion.

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II. SELF-ORGANIZING MAPS

A Self Organizing Map is one of the most popular neural network models which belong to the category of competitive networks. It is based on Unsupervised Learning, wherein no human intervention is required during the learning phase and the characteristics of the input data need not necessarily be known i.e. we make use of the SOM for clustering data without knowing the class memberships of the input data. The SOM which is used for the purpose of detecting features inherent to a particular problem is known as a Self-Organizing Feature Map (SOFM).A SOM provides a topology preserving mapping from high dimensional space to map units or neurons which form a two dimensional lattice. Topology preserving mapping connotes that the mapping conserves the relative distance between all the points i.e. points which were initially in the vicinity of each other are mapped to nearby map units in SOM. The main goal of the SOM is to transform an incoming pattern of arbitrary dimensions into a one or two dimensional discrete map. Each output neuron is fully connected to all the source nodes in the input layer. This network represents a feedforward structure with a single computational layer consisting of neurons arranged in a one or two dimensional grid. The topology of the grid can be square, hexagonal, etc. In this paper we concentrate on a particular type of SOM called the Kohonen's Network. Such an SOM has feedforward structure with a single computational layer arranged in rows and columns.

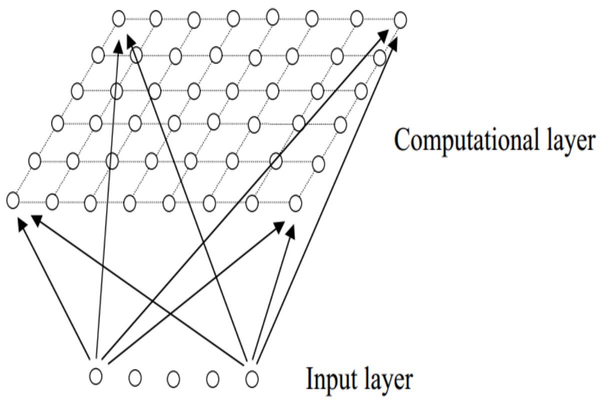

Fig 1: Kohonen's Network

A. Algorithm for SOM

The major components used in the algorithm include:

1. A continuous input space of activation patterns that are generated in accordance with a certain probability distribution.
2. A network topology consisting of a number of lattice neurons, which collectively

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defines a discrete output space.

3. A time-varying neighborhood which is defined according to a winning neuron i(**x**).
4. A learning rate parameter that starts at an initial value η_0, which then decreases gradually with time, n, but never reaches to zero.

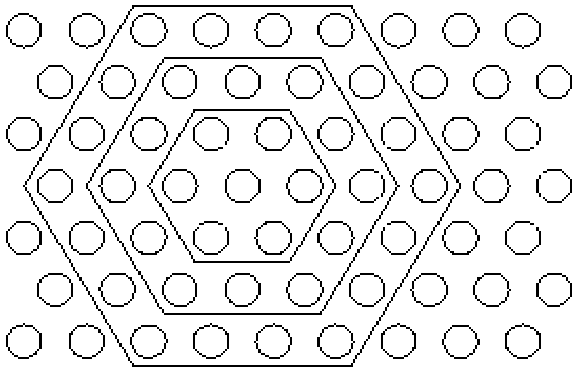

Fig 2: Neighbourhood of a given winner unit

The self-organization of a network involves four major processes:

1. Initialization: All the connection weights are initialized to random values.
2. Competition: For each of the input patterns, a discriminant function is computed by the neuron which provides the basis for competition. The neuron with the smallest value of discriminant is declared the 'winner'.
3. Cooperation: The winning neuron now determines the spatial location of a topological neighborhood of excited neurons, thus formulating the foundation for cooperation among these neurons.
4. Adaptation: The excited neurons decrease their individual values of the discriminant function in relation to the input pattern through suitable adjustment of the associated connection weights, in such a way that the response of the winning neuron to the subsequent application of a similar input pattern is enhanced.
   There are precisely two phases of this adaptive process which can be comprehensively identified:

- Ordering or self-organizing phase: During this phase, the topological ordering of the weight vectors takes place. Here, careful consideration is needed to be given to the choice of neighborhood and learning rate parameters.
- Convergence phase: during which the feature map is fine-tuned and comes to provide an accurate statistical quantification of the input space.

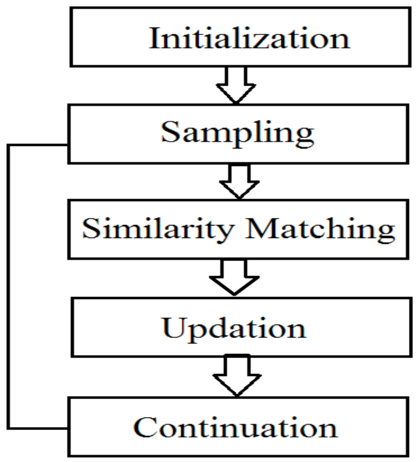

Fig 3: Steps involved in SOM

The operation of the SOM algorithm is represented as a series of the following steps:

1. ***Initialization:*** Random values are chosen for the initial weight vectors $w_j(0)$.The weight vectors of all the neurons must be distinct and the magnitude of these weights is preferably a small value.
2. ***Sampling:*** A sample x is drawn from the input space with a certain probability, this vector x represents the activation pattern applied to the lattice. The dimension of x is kept equal to m.
3. ***Similarity Matching:*** The best-matching i.e. winning neuron i(x) is found at time step n by using the minimum Euclidian distance criterion.
   $i(x)=\arg\ \min_j\|x - w_j\|$ where, $j=1, 2, \dots, l$
4. ***Updation:*** The synaptic weight vectors of all the neurons are adjusted using the following formula:
   $w_j(n+1) = w_j(n) + \eta(n)\, h_{ji(x)}(n)\, (x(n) - w_j(n))$
   where,$\eta(n)$: learning rate, $h_{ji(x),}(n)$: neighborhood function around the winner neuron i(**x**), $\eta(n)$ and $h_{ji(x)}(n)$ could both be dynamically varied for obtaining optimal results.
5. ***Continuation:*** Step 2 is continued until some noteworthy changes are found in the feature map.

III. PROPERTIES OF SOM FEATURE MAPS

The Feature Maps of SOM have four properties:

Insight into Input Space – Representation of feature map in the output space by weight vectors gives way to a good ballpark figure to the input space.

Topological arrangement - The feature map is such that a particular field of the input patterns is represented by the spatial location of a neuron in the output grid.

Density Matching - Alternations in the data of the input distribution are mirrored in the Feature Map as well.

Feature Selection - The SOM selects best attributes for estimating the non-linear distribution of the input data.

IV. EVALUATION OF SOM

The advantages of SOM over other approaches which are simpler are various though not blatantly obvious. The SOM has a major benefit that it never tires of learning and is flexible to new input, to which it readily adjusts itself. Also, the SOM neural network is efficient enough to learn all by itself, even when the system is not completely defined, thus it is well suited for applications where the relation among the inputs is unidentified. Another advantage is that SOM is potentially suitable to parallel computation since it doesn't need much inter-neuron contact. There are other advantages of SOM like easy interpretation of mapping, speed, easier computations, ability to organize large and complex data, deterministic duplicable outcomes, etc. The major drawback of SOM is its lack of definition in terms of mathematical models, network parameters and mapping. Therefore, solution is approximate without any guarantee of correctness and doesn't seem like a good choice for well-defined schemes. Apart from this, SOM also has other disadvantages like clustering due to mapping, inept organization and visualization, inability to decide upon the input weights, heavy dependence on the initialization, etc.

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V. IMPLEMENTATION OF SOM BASED RECOMMENDER TECHNIQUES

SOM algorithm forms a projection of high dimensional data onto an array. These arrays are referred to as nodes. Euclidean distance is used to measure the distances between pairs of nodes in the array. The regular array will henceforth be referred to as a "map". For each node, a reference vector is associated and this reference vector in the map is retrieved using the index of the node. The reference vectors are initialized for each node by picking random samples from training vector. One random data vector will be selected from the training data at a time and it is shown to the SOM whereby currently best matching node (BMN) is directly found. Also, the reference vectors for BMN and for nodes in its neighborhood are adjusted to become similar to the sample. The BMN for sample data vector is found by calculating Euclidean distance between sample and each node's reference vector. The node whose reference vector is nearest to the sample is chosen as BMN.

A. SOM User Based Collaborative Filtering

This technique makes use of the neighborhood preservation of data in order to retrieve similar users for the active user. The active user's neighborhood is determined by users having the same BMN and the users having their neighboring node as the BMN. A constant can be used to specify the radius within which neighboring nodes of the BMN can be found. Consider each user u having user rating model u_r, and each item i having an item rating model i_r, then the active user's neighbors are computed to be all the users u in the BMN and its neighboring node.

B. SOM Item Based Collaborative Filtering

This technique is based on rating data. It makes use of the neighborhood preservation of data in SOM in order to retrieve similar items for the active item. The active item's neighborhood is determined by the items having the same BMN and the items having their neighboring node as the BMN. A constant can be used to specify the radius within which neighboring nodes of the BMN can be found.

VI. AN EXAMPLE OF MUSIC ARTIST REVIEW USING SOM

We will explain a content based approach mentioned in the paper (Vembu and Baumann, 2004). Their idea was to use the music artist review from Amazon website and extract words from the reviews to build the artist profile.The general techniques of text retrieval are used and vector space model and tf-idf weighting schema are also used. The SOM algorithm is used to cluster the artist profiles represented as a bag-of-words. The documents which were created from the Amazon reviews contained words which are assigned a weight according to the tf-idf schema. 324 words dimension were selected, that were thought to have extra importance and it was given extra weight in the artist profiles. The feature vector was drastically reduced by removing words that were present in less than 5% and more than 90% of the collection. After the training phase, each of the map units represented a model from the collection of reviews in high dimensional space. The entire data collection was then divided according to the map models and were spatially organized based on their similarities. The system was assessed by comparing its results against a web based recommendation system. Each of the BMN contains the artists similar to each other based on the artist reviews. The top ten list generated by the web for each artist is compared to the BMN of the artist. It was observed for this system that if the top three or top five BMNs are included, the overlap between the top ten list and the artists' neighborhood increases. This takes place due to the map's self-organizing property wherein neighboring nodes represent similar data.

VII. CONCLUSION AND FUTURE WORK

In this paper, we have discussed a popular neural network model that is Self-Organizing Maps, comprehensively including their key features, algorithm used for their implementation along with an evaluation of their pros and cons. Along with these aspects, we have also focused on the application of the SOM for implementation of Recommender Systems. Recommender Systems today have seen a massive increase in demand due to information overload which has been plaguing each sector of the e-commerce industry. The presently existing methods have certain shortcomings which have been overcome by the use of SOM for the purpose of unsupervised learning. The SOM is a new-age algorithm which never tires of learning, is flexible to new input, is relatively faster as compared to its alternatives, has the ability to organize large and complex data and many more.
Upon analysis, we have deciphered that this approach also has its set of drawbacks like its lack of definition in terms of mathematical models, network parameters and mapping, inability to decide upon the input weights, heavy dependence on the initialization etc. But, the advantages of this system outweigh its disadvantages by a substantial margin. The examples illustrated in the paper make it obvious that the use of this technique would lead to major advancements in the degree of personalization and the preciseness of the recommendations which will in foresight enhance the performance of recommender systems to a great extent.

Due to the immense scope of this technique, it would be a beneficial decision to delve deeper into this relatively nascent technique. Algorithmically different SOM techniques like hierarchical SOMs and growing SOMs could be investigated to see if they can contribute to making the interface even more interesting without losing any of its current capabilities. Also, the possibilities of using a spherical SOM to increase the intuitivity of the maps could be researched upon. In terms of recommender systems, the genre of Music Recommender Systems has not evolved beyond a certain extent. They could be further explored in the future. The usage of newer techniques like the SOM and its variations along with contemporary techniques like collaborative tagging, integration of social network activity to influence the recommendations is the way to go for truly personalizing and enriching the user's experience.

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