



A Survey on Fashion Recommendation Systems

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Abstract: This study focuses on a recommendation system for a fashion company that sells online and offline products the type of products are similar in both ways, either online or offline and the quality of products is based on seasons. Product evolution is based on customer choice. Customers mostly buy products if they like and want to repurchase and the second is to try something new which is not on their list the demand for products is changing according to customer behavior. This research proposed a precise review of fashion recommendation systems for the collaborative filtering (CF) approach which identifies and filtered out the selling of products in higher quantity on both online and offline scales. It also filters the demand for products with respect to change in time and uses Singular Value Decomposition (SVD) for item-based factorization to find the most hit and visited products for future consideration and to improve its accuracy. This review focuses on the appropriate screening techniques and the various models that can be used in the development of referral systems. This review paper will benefit those who wish to contribute to the area of computer vision, machine learning, and various mode recommendation systems.

Keywords: Recommendation System, content-based filtering, Collaborative Filtering, customers, E-commerce

I. Introduction

Fashion is always a sense of aesthetics to improve a personality, the most adorable band under fashion is dressing. This research aims to build a recommendation system where customers can state their articulations for top brands Fashion tells more about the person's personality and how he/she carries herself/himself. It is a more authentic way to express garments, watches, shoes, hairstyles, makeup, perfume, etc. Fashion is a daily occurrence and has a direct impact on your profession, relationships and culture. People are very demanding as far as shopping is concerned. The main difficulty is selecting which brand has better quality at an affordable price. Recommendation systems are designed for computer-based intelligent technology to assist individuals by providing guidance and solutions these systems are valuable for patrons as well as merchants. Two main highlighted features like [2, 55] customers and items, customers are an important entity that leaves their reactions against products, moreover the reactions are recorded to express the ratings from all users to filter it out. Data scarcity is a term that has a greater impact on referral systems, particularly where the number of opinions and comments is insufficient to justify and recommend. Our focus on SVD has recently been recommended by many scientists to generalize their filtering and element-based predictions. Fashion always plays an important role in terms of facilitating people in various fields such as food movie purchases, etc. In general terms, hobbies of two friends can be found as a similar or strong positive correlation

Our research is based on different sections where each section is structured like background knowledge and history of Recommendation systems, Section 2 highlights the literature

review and the performance of recommendation systems in terms of collaborative filtering algorithms, which will be discussed further to support our proposed methodology.

Singular Vector Decomposition (SVD) is a matrix factorization approach that assumes $m \times n$ with r . $SVD = U \times S \times V$ here U and V are two orthogonal matrices with equal dimensions, hence S is read as a singular matrix, the same dimension for orthogonal matrices like $m \times m$ or $n \times n$ are non-negative real numbers. This consideration for m number of users and n number of items is part of the matrix. Starting diagonal entries can be considered as $A = (a_1, a_2, a_3, \dots, a_n)$ where each next value is greater than to the adjacent values like $a = 0, a \geq a_1, a_2 \geq a_3, \dots, a_n$.

SVD is widely used for information retrieval to check the similarity in terms of meanings hidden in words. This technique is adopted to examine the problems of those words which have usually the same meanings. This common issue can be seen [1, 17] while purchasing fashion products as the demand for products and their deliberated description and reviews are affecting the next customers and another major aspect is the timely [17,18] delivery likeness of the products. Customers buy seasonal goods, but other references are not directly affected by the seasons like books. Online purchasing of products is checked widely by customers where they can potentially review the products in comparison to discussed comments relative to those products. Different companies like Amazon, Google, Facebook, Netflix, and Twitter [14,22,23] are using recommendation systems as their business parts. Broadly categorization of recommendation systems is content-based systems and collaborative filtering systems

[1,23,18] along all there [16,18] can be various segments to describe recommendation systems, knowledge, content, collaboration, demographic, hybrid, and community. These all methods are classified in various ways for recommendation techniques. A vast variety of datasets with images are [18,29] used by researchers to contribute to the domain of recommendation through deep learning techniques as well.

A. Motivation

The recommended period said is [7] initially started in 19 based on one of the progress of large-scale research. Recommendation systems have been provided for the predetermined scoring structures. The first recommendation was materialistic in 1992 by Goldberg, Nichols, Oki, and Terry. An electronic messaging system Tapestry was built to allow only users about product quality and service as in good or bad, but now a lot of methods are introduced to count products and services through the internet. We can review and recheck customers and dislike towards any product through voting, tagging number the of visits, and the number of like and dislike too, or even reviews can be that taken me idly from different resources like YouTube videos, vlogs, and blogs. This review document will be beneficial for those interested in contributing to the area of computer vision, machine learning, and various mode recommendation systems.

In the early 2000s, fashion recommendation was implemented by electronic commerce, while in other fields such as education and fashion, recommendations were made based on previous history. Today, recommendations based on a vision are well known. Key contributions to this research include:

- We study between traditional simple targets and multiple targets to require performance.
- We investigate between traditional simple objectives and multiple objectives to demand performance.
- We provide abstracts and helpful advice to researchers to summarize and provide advice in the era of fashion recommendations.
- We reviewed the initial review of recommendation requests and their challenges and weaknesses.

II. Recommendation System

Recommendation systems are designed on the scale of the customer's interest in any product and they can be referred to as decision-making. Recommendation systems (RS) have been referred to as [7, 22] e-commerce tool referral systems are primarily designed in different fields such as education, entertainment, healthcare fashion industries, etc. We basically check the relation between users and products on the past ratings [2, 9, 17] most recommendation systems have data sparsity and cold start which is affecting results and can bring

negative accuracy. (B.SrikanthV.Nagalakshmi, 4, April – 2020) Recommendation systems are creative and innovative solutions to minimize the e-commerce service limitations as these systems are used to analyze the customer's behavior and information for actively demanding products from the customer's side.

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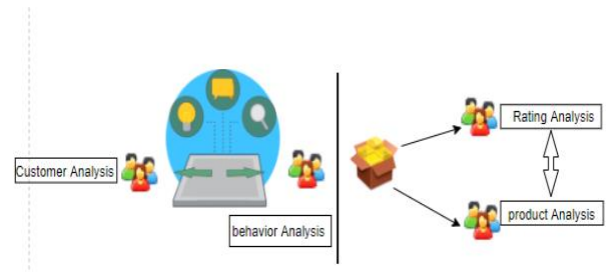


Figure 1 User-to-user and item-item approach in SVD

Categories of Recommendation Systems

A. Collaborative Filtering System

Collaborative filtering is a technique used to filter out the [19] products on the basis of other customers' reactions. This technique is used for automatic predictions of the interest of different customers and their preferences, moreover, we have two types of collaborative filtering systems. First, the user-to-user, this type checks the similarity among the users. This approach can be analyzed [19] by computing the cosine similarity and conditional probability. Secondly, item-to-item, it checks the relations among items of other interest items. It recommends most choosing products by similar customers, similarity is calculated on the basis of product rating, and for similarity checking correlations and cosine similarity is used.

B. Content-Based Recommendation System

Content-based recommendation systems that recommend items upon user interest. This system is used on a larger scale in various domains like television shows, restaurants, websites, and many items that can be sold. So the previously likely items are traced to recommend the future items on the

reaction of the other’s product, and preferences are noticed in database features.

C. Working Mechanism of the Recommendation system

There are various phases involved in the recommendation system like [7,14] the information collection phase, learning phase, and recommendation phase. It clears that the rest two phases are followed by the first phase, which is an information collection phase and the last phase [7] highlights that recommendations are made when the information is purely collected in the first phase, information collection phase.

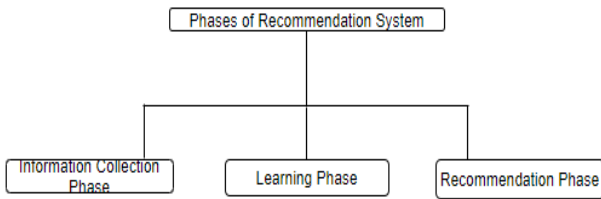


Figure 2: Phases of Recommendation System

D. Phase-1 Information Collection

At phase-1 user profile is generated on the basis of their behavior and act like browsing, like and dislike or the content they are interested in. Recommendation agents [16] can only make it possible to recommend accurately once the model is constructed well off.

E. Input in Recommendation System

Recommendation systems are based on three types of inputs as implicit, explicit and hybrid. Each of feedback depends upon users input and reaction towards the product.

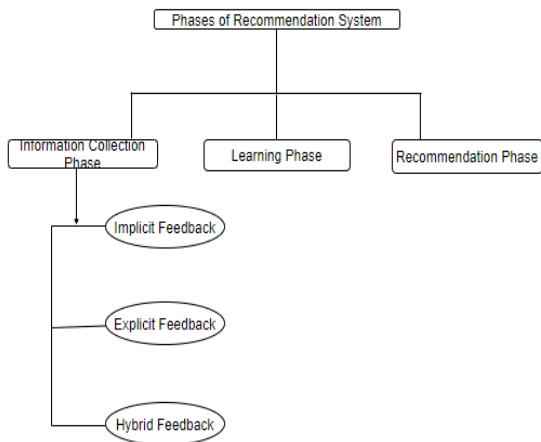


Figure 3 User Input in Recommendation system

F. Explicit Feedback

Explicit feedback depends on rich quality and interest in products and the accuracy is depending upon the user’s reaction against products, hence user’s reaction is very important to provide against each product as it will take an active part in improvement in accuracy rather an accuracy can be limited if the reaction is not produced.

G. Implicit Feedback

Implicit feedback is produced through indirect observations of user behavior as it functioned differently from explicit feedback and has less accuracy level.

H. Hybrid Feedback

Hybrid feedback is considered a combination of explicit and implicit feedback. Performance of implicit feedback is taken to validate data while the user’s reaction can be taken from explicit feedback.

I. Phase-2 Learning Phase

Learning phase work on the basis of the phase-1 information collection phase as it uses a learning algorithm to filter the user’s behavior collected in phase-1. This phase helps to construct [14,16] such patterns which can lead in the next phase.

J. Phase-3 Recommendation Phase

It recommends [7,14] what items are preferred by users as it can be taken from the information phase that can be modeled or memory based or the data browsed by users hence the recommendations can be made on the basis of the user’s history. In addition, way of hybrid feedback can be taken to compare the user’s demand based on content and likeness.

III. Classification of Data Mining Techniques

Data mining techniques are expressed from data where various data mining techniques are implemented [27] to extract meaningful patterns and rules for the predictions and decision makings. Various researchers have contributed to using of different data mining techniques to improve the performances of recommendation systems. Different categories have been examined in the classification of data mining techniques like, clustering, decision tree, association rules, neural network, regression, k-nearest neighbor, link analysis, and heuristic methods.

A. Clustering

Clustering is used to identify the clusters in describing [7,14,21] data where the same data points are discovered in groups and the division of those groups is also based on data points that a group can have. In addition, clustering can be divided into two types, hard clustering and soft clustering. Hard clustering is where data points can be exactly members of a group or they cannot be. While in soft clustering, we

assign data points to a cluster on the basis of the probability or likelihood of those data points.

B. Decision Tree

A powerful technique [3, 14,22] for prediction and classification holds the branching structure where each internal node carries a test on an attribute. It performs less computation for classification and has an understanding of rules which hold continuous and categorical variables.

C. Association Rules

Association rules are used to derive correlation and co-occurrences [7,14] among sets of data points. These rules are used to discuss patterns that encounter the repetition of items in a transaction. These transactions hold items like X and Y to check repeated patterns in both items.

D. Neural Network

A neural network shows an image of the brain for information processing. [2,5,7,14] These concepts are constructed from the inspiration of medical science to represent how the brain actually works. The concept of neural network systems is encouraging in the application of forecasting and business classification. This promising system behaves on the learning behavior from data,

E. Regression

A data mining technique which is used to predict continuous values as it involves pre-defined values from which new values are to be predicted. Regression supports [14] two basic types, linear regression, and multiple regression model. Linear regression is in the simplest form of regression which endeavors a relationship between two variables to observe the data. If the resultant graph is in the form of a straight line so it is assumed a linear model or if the resultant graph is curved so thus the model is nonlinear. In addition to multiple regression, it uses two or more two independent variables to predict results for the single continuous dependent variable.

F. Link Analysis

Link analysis searches [36] relating among large databases, as it supports sociological approaches to measuring linking scale among social users as it empowers the accuracy of web browsing and enables the investigator to spot association patterns

G. Heuristic Methods

Heuristic methods are used to get [14,18,23,39] optimized results and solve problems rapidly whereas many new methods are added up to present methods that are enough strong to show up results within time frames.

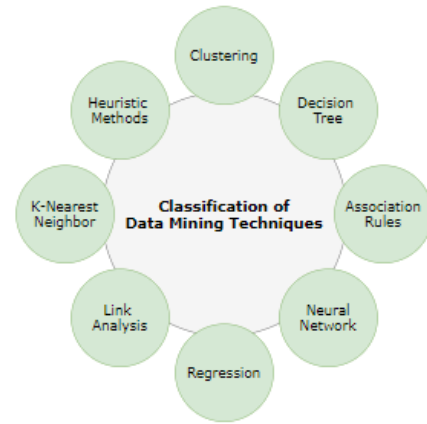


Figure 4 Classification of Data Mining Technique used in traditional and modern models

IV. Literature Review

A. Traditional and Modern Models for Recommendation System

Most relevant work is carried out by [5] to present an implementation on fashion industries that sell fashion products in both ways online and offline. Therefore, the products are identical in both physical and online locations. The researcher has analyzed the customer's demand on the basis of two factors, the first products are mostly liked according to the seasons and the second products are repaying [3,9,11,27,45] because of their previous likeness. Clothing AI is an AI-based fashion recommendation system that uses machine learning algorithms to provide customers with personalized fashion recommendations. The system collects data from customers' purchases, browsing behavior, and other information [40.52.53] to create user profiles. It then uses this data to recommend the best clothing items for each user based on their individual preferences.

Clothing AI is quickly becoming one of the most popular fashion recommendation systems in the world. Many leading fashion retailers are utilizing it to provide customers with personalized shopping experiences. It is also being used by fashion influencers to help their followers find the perfect fashion item for their style. Fashion recommendation system that is changing [19,24] the way we shop for clothes. It uses artificial intelligence to provide customers with personalized fashion recommendations [50,52] based on their individual preferences. To present their work author has used K-RecSys which focuses only item-based collaborative filtering. Here the main motive is to check the weightage of the most hit products online and sell products offline. This approach is carried out to measure changes in preferences with respect to time.

Recommendation System provides a number of benefits for both customers [21,26,29,36] and retailers. For customers, it provides personalized fashion recommendations that are tailored to their individual preferences. This allows customers to find the perfect clothing items for their style. Another research conducted by (Wang, 2019) where they used (SVD) ++ algorithm for good prediction performance their elaboration on a large dataset they criticized the performance as it targets the speed of converging of model performances. The proposed function, ALR, is designed to gather exponentially with linear functions as it performs better on convergence speed. Work proposal on (XU YU YU FU, October 5, 2018,) cross-domain recommendation algorithm is based on feature transfers and imbalanced classification problem. The author focuses on feature extraction by Funk-SVD model from auxiliary domains.

Work carried out by researcher (Xiong Yaohua, 2018) is to propose a recommendation system based on SVD Collaborative Filtering as the rating matrix is computer either between 0 or 1 on the basis of change in weather. As it checks the similarity in pictures which have been used in the past records that the new images are based on previous style or not. Sparse Decision Making [6,18,34] is a big such problem facing recommendation systems so the researchers have proposed accurate sparse decision making model with two ways in Artificial Intelligence enable IoT systems. This model presents trust and rating information to deal this issue under SVD++, hence the accuracy has reached to maximum 29%.

Matrix Factorization method [2,19,27] referred characteristics of the user based approach as well as an item based approach, this model has achieved fame in recent times due to higher accuracy, simplest implementation, scalable and flexible in the domain of recommender systems. It is even useful in the matrix dimension reduction with specialty of data sparsity and noise filtering. Recommendation systems are [14] designed to provide user's problem solution and the paper discusses different potential and prediction techniques in recommendation system for a better practice in the field of recommendation system. Recommendation systems are to made for assisting [17] when no such experiences work for personal knowledge and to handle those issues that user faces usually [18,19] so the recommendation systems are developed to replace the problems with solution as it counts collaborative filtering, content based filtering or hybrid filtering.

Collaborative recommendation systems are designed and implemented in various fields. Collaborative filtering is

[19,35,38] also used in an online social information filtering system in terms to construct user's profile. Ringo an online application is also part of this collaborative filtering, which is used for building user's profile for the domain of music albums. It can be used by fashion retailers to provide customers with personalized fashion recommendations. It can also be used by fashion [19,21,26,30,36] influencers to help their followers find the perfect fashion item for their style. Additionally, Clothing AI can be used by fashion designers to develop better designs and create more effective marketing campaigns. Amazons are [21,27,28,29] using multiform algorithms to broaden a user's scope. This kind of system is using collaborative filtering methods to manage the issues which are produced by similar item where items are compared with item to item comparison and the new results are generated on the basis of the user's previous history.

In addition to content based techniques which are also used and produce predictions on the basis of user information and this method avoids the technique of collaborative filtering. On the other hand, both discussed techniques have a successive role and limitations too. Said limitations are linked with content-based filtering techniques where data sparsity is highlighted and affects in the generation of results. In reference to collaborative filtering, it also hits the problem of cold start where no sufficient data is collected to ensure results for users. If the problems remain in the modeling system, the recommendations quality may affect. For the improvement of [22,23] of such a problem we can implement hybrid filtering, which supports different techniques at once to improve recommendation accuracy and performance. The benefit of using hybrid filtering is that it can tackle problems and improve weaknesses.

The combination of collaboration and information filtering was proposed by [25] for integrating collaborative and content based filtering. Recommendations are basically designed to [15] facilitate users in various manners under complex environment for their hits like and interest [1,11,27,44] towards products. Collaborative filtering (CF) is fully fledged and implemented technique. Luckow et al. [50,51,52] presented automotive dataset which helps in identifying automobile's properties where they have observed both process like manufacturing and accuracy for the Convolutional Neural Network (CNN) and computer vision classifier during the analyzing researcher have observed that implemented classifiers have effective accuracy.

Singular vector Decomposition is a matrix factorization technique based on rectangular matrix A with m number of

rows and n number of columns respectively. Amazon is using Clothing AI to provide [11,15,24] customers with personalized fashion recommendations. The system is able to recommend the best clothing items for each customer based on their individual preferences. The recommendation systems basically target the inference of users on different products for the selection of users and their behavior against products. The domain we focused on here is user-item rating. Each item can be considered as a q vector, in order to remove noise from large data we have used supportive techniques.

Though the proposed approach is a complex matrix computationally hence it provides a cheap rank on a linear approximation of the original matrix. We have taken the value of k as a single value which will behave according to the size and structure of data. A fashion retailer that uses RS to provide customers with personalized styling [19,27] services. The system is able to analyze customer data [19,25] such as purchase history and browsing behavior to recommend the best clothing items for each customer. To implement this approach initially we have to compute the k value so the matrix value like U and V which can be reduced to make matrix like $U_k V_k$. First matrix is calculated from removing columns (n) and rows (m) from original matrix, after elimination we will get a new value A_k . We have computed [12,19,37] this new value of A from closest approximation. This change in the value of A ensured the noise removal from data.

To fashion recommendation system same types of clicks on products are mapped on a similar scale. $A = U \times S \times V$ This shape of the equation can be seen before changing the value of A . Change in value of A is shown as $A(m * n) = U(m \times m)S(m \times n) V(n * n)$, here $U=m * m$ and $V=n * n$. Columns which raise from U are left singular vector where V is right singular vector. SV methods are mainly used for two major aspects (1) how prediction accuracy can be improved and (2) how to maximize calculation efficiency.

Researcher whose contributions for [9,20,41,44] medical image classification where they have used Decision Tree Induction algorithms, Convolutional Neural Network (CNN), Neural Network, Nearest Neighbor and support Vector Machine (SVM) to gain promising performance and examined that implication of Deep Learning can provide predictive results and accuracy along with this image dataset is also highlighted to affect accuracy and performances of implemented techniques.

Ferdos Fessahaye et al. [7,11,13,19] contributed for music recommendation systems using deep learning approach where they have proposed a technique to improve music recommendation system which can be used for YouTube videos, Netflix movies and Amazon shopping researcher have

proposed Tunes Recommendation system (T-RECSYS) based on hybrid of content based and collaborative filtering for deep learning classification models to predict accurate accuracy and recommendations with real time predictions.

Proposed system follows 9 songs which are liked by users in together the next song can be liked or dislike by users as per their preferences so it will be ranged between 0-1 its decision can be made on the past records of 9 songs that the next 10th song will be preferred by the user or not. Xinxi Wang et al. [7,20,50] Proposed system which works in both conditions cold star and warm start without affecting collaborative filtering (CF) other than it also works in an efficient hybrid manner for improving collaborative filtering performance and pushes back the previous traditional feature based method.

Recommended System Approaches in Past Decades

Approach	Recommended System	Year
Content Filtering	Mafia	Early 90's
Collaborative filtering	Tapestry	1992-1998
Data rating	GroupLens	1992-1998
Dataset construction	Movielens	1992-1998
Collaborative filtering	Probabilistic latent semantic Analysis	1999-2005
Collaborative filtering	Probabilistic latent semantic Analysis	2005-2009
Mixed technique of content and collaborative	SVD, RSVD and NSVD Context Aware based	2010 till now

Figure 5 Recommendation System Approaches in Past Decades

V. Algorithms Used in Developing Fashion Recommendation System

More frequent and used algorithms in [7,12,14] development of recommendation systems are Multilayer Perceptron (MLP), Recurrent Neural Network (RNN), K-nearest Neighbor (KNN), Bayesian Network (BN), Autoencoder (AE), Convolutional Neural Network and Generative Adversarial Network (GAN).

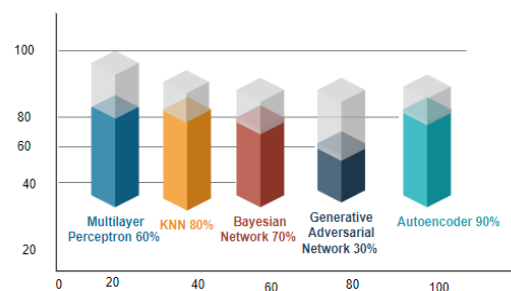


Figure 6 Accuracy performance of different algorithms over different datasets

Researchers have put their efforts in using these algorithms to improve accuracy. Furthermore, these applied methodologies are discussed below.

A. Multilayer Perceptron (MLP)

It is an architecture of Artificial Neural Network (ANN) which is based on a sequence of layers which can be infinity in number in building of neurons. Neurons can measure and compute the weighted sum of its inputs to perform signal activations functionalities. These signals are transmitted in further neurons. These neurons work in a manner to produce human like responses. Artificial Neural Network (ANN) is used for non-linear problems where responses can be generated from training sets. This computational model is designed to perform classification, prediction and decision making tasks. Additionally, Artificial Neural Network (ANN) is composed of more than three layers that are input layer, multiple hidden layer and output layer.

B. Recurrent Neural Network (RNN)

Recurrent Neural Network (RNN) is a generalized type of neural network with internal memory which is functionally active to follow series of inputs/ these inputs and generated outputs are depending on the nodes and research type but not inter dependents. The size of inputs may vary dimensionally whereas hidden memory may be different from one to next cells. ReLU is the common function used in RNN beside LSTM Long Short Term Memory is the extended version for RNN which is to store previous records in memory. It is used in classification and prediction time series data. A session based recommendation system was designed by a researcher to produce results on past click and history records by using Recurrent Neural Network (RNN) same way the efforts of another researcher to suggest hierarchical Recurrent Neural Network (RNN) to deal with session recommendations for input and output layers whereas conditional RNN is used to develop a recommendation system based on context aware as well as session based. A clear approach in the fashion recommendation system is proposed by [45] where bidirectional LSTM Long Short Term Memory is used to predict results on past items and their relationship. An attention based LSTM recommendation system was proposed by for hash tag recommendations.

C. K-nearest Neighbor (KNN)

A supervised machine learning algorithm K-nearest neighbor (KNN) is a [14,21] simple and important algorithm to handle both classification and regression problems, as it has important aspects as it works easily and interprets results, quality time is required for the calculation. KNN works effectively for recommendation systems and it supports three phases, where in phase (1) it builds up the user's profile from past inclination rating while in phase (2) it applies machine learning techniques to know k number of users who have the same nature in the past history so the degree of similarity can be marked. And in phase (3) recommendation systems build users' likely purchases of items for which neighbor has expressed their likeness and willingness. KNN algorithm obtains most homogenous items by applying different similarity measures like cosine, Euclidean correlation coefficient, and many more. Viriato De Melo et al. Proposed content-based approach with a combination of textual attributes, visual features, and human visual attention for clothing recommendation.

D. BAYESIAN Network (BN)

Bayesian networks are type of [14] probabilistic graphical model used for prediction, detection, diagnosis, decisions, and reasoning. This type of network is consisting of directional nodes and links where each node is representing a variable which can be any figure so the variable can be called as multivariable node. The type of variable can be discrete and continuous. Bayesian networks are used for modeling the joint probability distribution where each node is a representation of a random variable whereas links describe the dependencies among variables. Movie recommendation and promotion model was developed by [55] based on context aware movie preferences, researchers have discussed the working of Bayesian network on recommendation and promotion model so they have computed movie preferences in different parameters like gender, age, mood, location, situation, direction, production and movie ratings.

E. Autoencoder (AE)

An unsupervised [7] learning technique for neural network, which works for efficient data and data training for signal ignorance, they are based on encoder, code and decoder whereas encoder and decoder are joint while code is a single layer for Artificial Neural Network (ANN). The working efficiency for the encoder is passing input to produce code while decoder produces output. Hence the input and output should be same in addition to a number of layers which are consisting on rate of compression, so as a minimum the number of layers is as maximum the compression ratio will be. The encoder can be [14] any variable among 2 and infinity

and we can need it as deep as we demand therefore these types of models are used most common loss function like mean squared error (MSE) and Binary Cross Entropy.

F. Convolutional Neural Network (CNN)

Convolutional Neural Network (CNN) is built by multiple convolutional layers which are functionally active to produce desired recommendation outcomes, these layers may vary in [7] convolutional layer, filter size and connected layers. Increment and decrement can take place to produce accurate responses. Convolutional Neural Network (CNN) supports optional pooling layer for data dimension reduction and the general pooling form is max pooling ranges among 2×2 and 4×4 . Similarly, the most common activation function in Convolutional Neural Networks is ReLU, TanH, Sigmoid and Softmax which can work in both manners individually as well as stacked form. Convolutional Neural Network (CNN) is well performed in recommendation systems as it can strongly work for feature extraction and image classification. Max pooling layer and convolutional is also used by a researcher to produce visual features from various mark of images

G. Generative Adversarial Network (GAN)

Generative Adversarial Networks are generative techniques based on Deep Learning where two different networks are used to produce more accurate outcomes. This model generates fake outputs against data that can be easily marked with a model that outcome is not actual. Generator network works simply on five layers where I the discriminator works in quite a different manner, thus it discriminates the class probability against input that can be in the form of an image. Clothing recommendation system which [12,28] can provide accurate outputs (clothing) to users.

Table 1 Summary of Research in the field of RS for Multi-Domain

Reference	Features	Domain	Approach	Result
Pierfrancesco Bellini et al.	User's Experiences	Brand Marketing	Multi Clustering Approach	Purchase be
Qurat Ul Ain et al.	User's Rating	Decision making	multi-dimensional conceptualization framework	pers exp recom
Santiago et al.	User's Trust	Health Interventions	Artificial Intelligence	Beha
Hyojung Kim et al.	Genderless Fashion Trends	Fashion Trends	Linear Regression Analysis	Consum Fa
Shanshan Wan et al.	Neighbor Behavior	Hybrid E-Learning	Sequential Pattern Mining	Structur D

Similarity Metrics

To improve recommendation models our work has made positive comments as a preference for new users on the basis of their most liked and visited items seasonally as well as previously desire. To calculate the similarity among the products we have computed distance generally to obtain mean values for each of the categorized items. We have categorized items in different segments like, segment-1 is for bags and segment-2 is for female-accessories etc.

a. Cosine Similarity

Cosine calculates the cosine of angles between two vectors. So as smaller the angle [13,18] is computed there a higher similarity is. Here the distance can be measured on the basis of the value containing for each category as segment-1 has 5 points and segment-2 has 7 points. We can analyze the distance by measuring cosine similarity.

$$\text{similarity}(two\ products) = \frac{A \cdot B}{\|A\| \|B\|} = \frac{\sum_{n=1}^n (A_n \times B_n)}{\sqrt{\sum_{n=1}^n A_n^2} \sqrt{\sum_{n=1}^n B_n^2}} \tag{1}$$

Correlation coefficient

It is reflecting the linear correlation among variables so as higher the coefficient the higher similarity is counted. For mathematical representation, we have:

$$\frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n(x^2 - (\sum x)^2/n)]} \sqrt{[n(y^2 - (\sum y)^2/n)]}} \tag{2}$$

b. Euclidean Distance

Euclidean distance is calculated for finding the similarities among two points, so as nearer the distance is among points the maximum similarity is. For Euclidean distance we can represent it as:

$$distance(a, b) = \sqrt{\sum_{i=1}^n (a - b)^2} \quad (3)$$

c. Normalization

Vectors are measured on a large scale, therefore they are normalized before any measurements. On the measurement scale, we have decided range between 0 and 1

$$u = \frac{u - (\min(u))}{\max - \min} \quad (4)$$

Evaluation Metrics for Recommendation System

To calculate the accuracy of a recommendation system some [14,16,22] recommendation algorithms are used which indicates metrics. These metrics are decided [5] on filtering technique types. Hence the performance and accuracy of a recommendation system can be computed by using Root Mean Square Error (RMSE), Receiver Operating Characteristics (ROC), Area Under Curve (AUC), Precision, Recall and F1 score. The mathematical expression for RMSE can be

$$RMSE = \sqrt{\sum_{l=1}^N (pr(users_items) - ar(user_items))^2 / n^2} \quad (5)$$

In Root Mean Square Error (RMSE), N is the total number of predictions, (PR) is the value for predicted rating and (or) is the actual rating

$$Precision = \frac{TP(TruePositive)}{TP(TruePositive) + FP(FalsePositive)} \quad (6)$$

Precision are positive predictive values with the purpose instance, in retrieved instances.

$$Recall = \frac{TP(TruePositive)}{TP(TruePositive) + FN(FalseNegative)} \quad (7)$$

The recall is also called the percentage of matching items from total items.

$$F1Score = 2 \times \frac{Precision \times Recall}{Precision + Recall} \quad (8)$$

F1 score represents the accuracy range between 0-1, where the values which are closer to 1 can be predicted as highly recommendations.

Hence, coverage is a measurement which is used for item recommendations by using algorithms. While accuracy is derived from the total and actual recommendations. It can be expressed as

$$Accuracy = \frac{TP(TruePositive) + FN(FalseNegative)}{TP(TruePositive) + FN(FalseNegative) + TN(TrueNegative) + FP(FalsePositive)} \quad (9)$$

Receiver Operating Characteristic (ROC) Curve represents a trade-off between sensitivity and specificity. The curve which hits the top left corner is called a better performance, whereas the curve at 45 degrees will be considered as a less accurate.

Comparative Evaluation of Fashion Recommendation systems and their Limitations

There has been notified improvement in recommendation system in recent time, which is beneficial for [12] consumer and retailers. In terms of various hybrid filtering techniques proposed for strengthening collaborative filtering and cold start issues are highly considered in the hybrid algorithm which mostly depicts [44] high sensitivity whereas hybrid filtering does not support on [12] collaborative data. In addition, it is considered as a drawback as hybrid made system composite in nature as it requires most of parameters and features important as in supportive angle it solves [43,50,55] sparsity problems of collaborative filtering (CF) by implementing multilevel technique. In comparison to content based filtering (CBF) products are recommended [17] on the basis of user's evaluation as this type of filtering does not support any past record of users to work efficiently in future times and recommendations moreover content based filtering works for the user's interest to recommend accordingly and attains quality in description for making any decision so the system is fragile for domain knowledge which is helping in to make possible recommendations and these recommendations are limited on the existing database which owns user's previous interest and experience so the major weakness under content based filtering is limited analysis as the users are only entertained for previously liked items no now user is recommended while collaborative filtering is not working on pattern of domain knowledge but it supports multiple users which does not attain [44] contextual attributes. Collaborative filtering generates new recommendations for users as it is less dependent on the previous record of users. Furthermore, it works similar to content based filtering (CBF) as it does not generate responses for collaborative filtering. Additionally, hyper personalization [7,41] requires auxiliary data to produce better results for user's satisfaction, but it makes the

process expensive and it may lead to privacy concerns as well as it needs data more than the requirements.

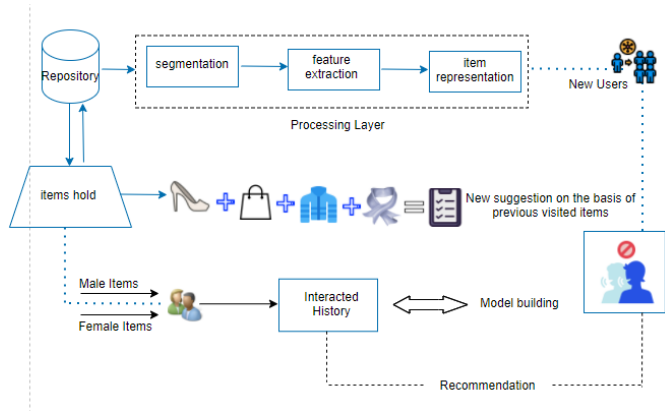


Figure 7 Depicts Recommendation Model for Data Flow in Fashion Industry

Reference	Year	Fashion Target	AI Model	Evaluation Metric(s)
De Devitiis et al.	2021	Recommendation Compatibility	Autoencoder (Memory Augmented Neural Network)	mAP Accuracy
Dong et al.	2021	Retrieval forecasting	Attribute Specific Embedding	mAP Recall
Hajjar et al.	2021	Clothing and Shoes Recommendation	Attention Model (Encoder/Decoder)	AUC Accuracy (log likelihood)
Jiang et al.	2021	Clothing Accessories	Generator Discriminator	User Study
Kuang et al.	2022	Clothing Shoes	Deep CNN and Ontology	User Evaluation, t-SNE
Laohakangv alvit et al.	2022	Classification of Clothing Accessories	Deep CNN	Accuracy, Precision, Recall, F1-Score
Lee at al.	2022	Not Mentioned	MLP, Visual Matrix Factorization	Hit Ratio
Pecnakova et al.	2022	Dresses, jeans generation	GAN, CNN	Precision, Recall, Expert Evaluation
Xhaferra et al.	2022	Clothing and Shoes Classification	Deep CNN	Accuracy
Chen et al.	2023	Conversational recommendation	BERT Encoder, GCN	AUC, Precision, Recall

Prakash et al.	2023	Friends Accessories	BERT Backbone, Context Aware Embedding	Precision
Selamat et al.	2024	Tag based Recommendation	CNN	Precision, Recall
Mateos et al.	2025	Cross Domain Recommendation System	Survey and Taxonomy Framework	Survey Paper

Recommendation Systems (RS) work of collecting data [14,22,48] from customers’ shopping behavior and preferences. This data is used to create user profiles which are then used to recommend the best clothing items for each user. To create user profiles, further AI uses algorithms to analyze customer data such as purchasing history, browsing behavior, and other information. This data is then used to create a profile for each customer. The profile includes information such as the customer’s favorite colors, styles, and sizes. Once a customer profile is created, Fashion Recommendations use machine learning algorithms to recommend the best clothing items for each user. The algorithms use the customer profile to determine the best items for each user based on their individual preferences.

a. Dataset Comparison over last 5 years

Reference	Dataset	AI Model	Achieved Accuracy
[45]	Deep Fashion	Attention based Embedding Model	70%
[46]	Rent The Runway	Attention and Encoder Decoder	73%
[47]	Fashion144k	Encoder/Decoder GAN Discriminator	Qualitative User Study
[49]	Deep Fashion2	EfficientDet	83%
[50]	Tradesy	Visual Matrix Factorization	62%
[52]	Fashion MNIST	Deep CNN	91%

Singular Value Decomposition is only suitable for collaborative filtering but gives the poor performance on image datasets. Therefore, in recent times the performance of CNN AND GNNs are high accurate.

K. Challenges in Fashion Recommendation System

Developing Recommendation systems can be a challenging [17,19,52] process. The biggest challenges are collecting the data necessary to create user profiles. This requires retailers to collect a large amount of customer data such as purchasing

history, browsing behavior, and other information. Another challenge is developing algorithms that can accurately recommend the best clothing items for each user. This requires complex machine learning algorithms that can analyze customer data and make accurate recommendations. Recent time has quality growth in fashion and aspects along with this noticeable achievement there are various issues and challenges faced in fashion industry, the top most challenge which is faced is [8] lack in data as the recommendation systems need bulk of data to produce recommendation for users as the well-known company's like Google, Amazon, Netflix have huge amount of data for production of excellent recommendations as the user's images, textual data, demographic records and any [13] cultural behavior and information whereas the development of recommendation system under these issues is very challenging to design up any framework within limited data. Image data is always a crucial part in recommendation system as the environment affects more on taken images, most of images are observed to be considered with low resolution and environment affects like street photos [32] and selfies with various postures which brings difficulty in prediction and recommendation while the photos taken with high resolution [22, 50, 55] have the higher accuracy in predictions and recommendations. Changing in data is also a very critical part of recommendation system as the users have different views and behavior against any product so it also builds difficulties to run recommendations it may also be varied due to frequent change in trend and weather which emphasize user to fluctuate their interest and likeness. Moreover, preferences are also a big challenge to deal in recent times. Users may search product items in terms to color, size, shape, style, brand, fabric material and quality. Preferences may change due to customer's mood, environment behavior, cultural behavior and demands despite this unpredictable product are also part of challenges in recommendation system as the reaction against [46,47,50,54] any product, movie, song and fashion can be difficult to predict and recommend accordingly.

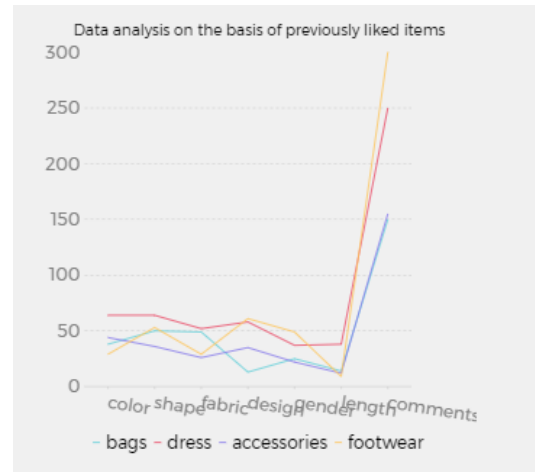


Figure 8 Previous Clicks from Recommendations

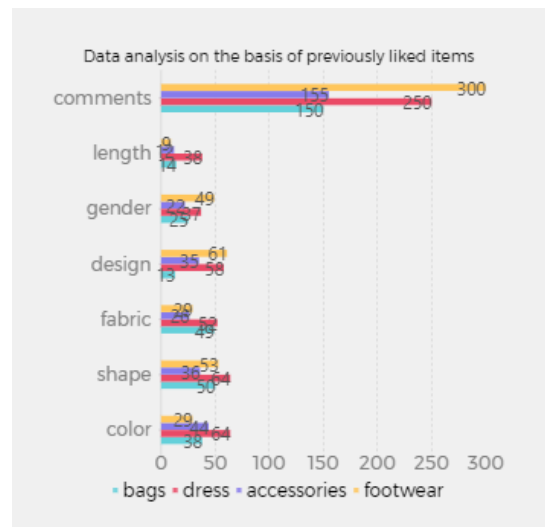


Figure 9 Data Analysis for Previously Liked Items

VII. Dataset

The dataset is picked from Kaggle used in different research papers by various researchers as one of dataset is related to fashion images with 11 attributes for men and women. The major attributes of datasets are id, gender, Master Category, Subcategory, article Type, base Color, Season, Year, Usage, Product Display Name and Image. Where each of the categories is finely classified in deciding benchmark dataset where 44447 features are added for each of the attributes and total 60000 images for said attributes. The prediction is totally dependent to human behavior against the products. Each of the pictures was classified into groups on the basis of id, gender, master category, sub category, article type, base color, season, year, usage and product display name. Each of the feature has a unique id against each product. Products are finely categorized by male female. Similarity between products is highly categorized by male and female where each of the dependent value separated by its category like accessories which holds top wear, bottom wear, watched

socks, shoes belts etc. Another dataset is Amazon Product Reviews

VIII. Conclusion and Future Recommendation

In this research, we have elaborated all methods for improving efficiency while using multiple ways on recommendation systems instead we have examined that various techniques within collaborative filtering and context based filtering to examine the importance of each contribution in the relevant field. We have also received good accuracy in terms to various fields by extracting previous liked items by users or their likeness towards product and the reaction against any item and product, in collusion it is to highlight that various ways can be implemented to get better results. In future further work can be extended to meet the challenges like features based image classification by using multiple algorithm and clustering technique will improve the research. The future of Recommendation Systems is very bright. As more and more retailers adopt the technology, Clothing AI will become more sophisticated and powerful. We will also see more applications of RS such as virtual styling and fitting rooms. We can also expect to see RS being used in the fashion industry in new and innovative ways. RS could be used to predict trends and make more accurate predictions about customer preferences.

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