Choosing the Right Model: A Comprehensive Analysis of Outfit Recommendation Systems

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ABSTRACT

This Survey unravels developmental research on Fashion Recommendation Systems. (FRS). There is an introduction to the the three types of Recommendation Systems that are present: Content based, Collaborative Filtering and Hybrid Models, and a discussion on their pros and cons. Then onto discussing the challenges faced by Recommendation approaches followed by specifically the ones by Fashion Recommendation Systems. The need for presenting Outfit recommendation models and the importance of their accuracy is presented. Finally, a comprehensive survey of 4 types of Fashion Recommendation Systems: 1.) Collaborative Filtering 2.) Content based 3.) Hybrid 4.) Ontology based. A presentation of these with examples for representative algorithms of each category, and analysis of their predictive performance and their ability to address the challenges is carried out.

General Terms

Fashion Recommendation, Predictions

Keywords

Recommendation System, Fashion, Collaborative Filtering, Content-based Filtering, Hybrid Filtering, Ontology, Deep-learning, Visual Features

1. INTRODUCTION

Recommendation Systems are being widely used and implemented in different online websites and applications as we progress through the 21st century. Recommender systems help users make effective choices aligning with their interests and behaviours or by considering item attributes or both [9]. These allow you to make valuable choices without surfing through all the options available every time. There are three types of recommendation systems, namely Content-based, collaborative filtering, and Hybrid based. Content-based filtering uses similarities in features to make decisions. This method revolves entirely around comparing user interests to product features, and the items that have the most overlapping features with user interests are recommended.

Collaborative filtering mimics user-to-user recommendations. The predictions are made as a weighted combination of other similar users' choices. Hybrid systems combine various recommendation techniques, sometimes along with machine learning or deep learning models, to make predictions or recommendations.

The fashion industry has started to implement recommendation systems in online outfit recommendation apps and e-shopping websites. The power and ease which personalised garment recommendation systems carry are commendable. The massive amount of fashion outfits in the market and online e-shopping sites can be a hassle for selecting outfits [6]. The exponential growth of e-shopping websites and their database has increased the need for recommendation systems. [9] It can benefit both the garment designers and the consumers of the industry.

First and foremost, the immense progress in society in terms of technological advancements has been the driver of change and changes in the social-cultural context to bring about developments in diverse settings [23]. In this fast-paced world, chasing each other in a rat race, time is of the utmost importance, so much so that time is equated with money. People do not have the time and attention span to go through the entire closet of choices [7] that is available to them through a plethora of websites [16]. Thus, the need arises to provide consumers with a personalised fashion style integrating the features of complex fashion structures, rich tones and diverse types of texture to give recommendations. Hence, fashion Recommendation Systems ensure a more efficient system and reduce the transaction cost of selecting and choosing items in an e-shopping environment. Providing quality recommendations would also improve both the quality and the process of selecting your desired apparel.

The critical contribution of this survey is to provide a qualitative and quantitative analysis of the different types of techniques implemented in fashion recommendation systems. Let us start by dis-

cussing the challenges faced while performing the Literature Review and then discussing the vast multitude of approaches.

2. CHALLENGES OF FASHION RECOMMENDATION SYSTEMS

The booming fashion industry is multi-faceted and occupies a significant position in the global economy. The clothing industrial chain includes garment design, production and sales. Fashion Recommendation systems usually operate in a challenging environment and are implemented using complex algorithms and techniques. Due to this, the recommendation systems are bound to face several challenges in the fashion domain which need to be resolved.

—Extracting features of clothes like texture, colour, length, collar, sleeve, etc is a huge challenge. Usually taking fine-grained visual features, further categorization of these basic features, of garments into account is a complex job. Deep neural networks like hierarchical convolution and AlexNeT (CNN model) are proposed to extract the fine-grained and extremely detailed features from the images of garments.

—To make generic outfit recommendation systems, body type is not an attribute that has been taken into account. Body type is also an important feature to be taken into consideration for a personalized recommendation system. The body type and customized feature selection for specific body types are taken into account as well [1]. Personal features like - body measurements, body types, age, facial features and a robust ontology-based recommendation system are also specified and incorporated [18].

—While handling expert knowledge and databases, it is evident that the vast information of the fashion industry is unstructured and not refined. Important attributes like garment properties, facial features, styles, and occasion for a garment are the fundamental blocks of fashion and clothing. It becomes very crucial to organise and structure the large database in the domain of fashion. An Ontology-based Recommendation system for outfits, which takes not only garment but also user attributes in a very structured form. [18]

—Parsing clothes efficiently and effectively is a very difficult and tedious job. It is hard to segment or distinguish clothes through only bottom-up image features. The variety of human poses and occlusions play a significant role in cloth recognition on the human body, making it hard to have a clear vision or an accurate frontal view. For accurate classification of garments into different categories, one can make patches of pixels from different datasets of images of outfits to label the features. [15]

—Refining and extracting fashion models and attributes from videos is very complex since the multimedia gained from virtual space is mostly not standard. Often, the background colour is interference in computing the colour tone of clothing. A more refined and structured fashion multimedia mining is required for inculcating all the features and attributes accurately.[3]

—Relevant recommendations or matches may depend on location, seasons as well as occasion which makes model learning in Recommendation Systems complex. In mobile shopping in the domain of Recommendation Systems, certain limitations like network capacities, memory and computational shortcomings are constraints that are very crucial and should be taken into consideration.[4]

—Common problems faced in recent works in the domain are cloth parsing, cloth recognition, cloth retrieval and clothing recommendation. Cloth parsing is pixel-wise labelling of clothing items which is fundamental to other tasks. Solutions to these problems are given in [13]. Clothing appearance is demonstrated by semantic attributes using a CRF based approach. A retrieval system using the colour and attribute information shows improved clothing retrieval results and solves the cross-scenario retrieval problem of similar items of clothing. The recommendation is solved by implementing a probabilistic model for learning information about fashion coordinates. Latent SVM based models for occasion-oriented recommendations were utilized to provide the user with information based on certain queries.[15]

—Existing fashion RS focus mainly on developing relations between products and consumers, completely sidelining considering fashion experts' knowledge and human perception of fashion products. Consumer perception, human behaviour and emotion play a significant role in the decision making of purchasing a product. [19] proposes a perception based fashion design recommender system that considers domain expertise, and user emotions and perceptions.

—Information from the past behaviour of the user may not be available readily since the users may not be willing to provide this rating. It is desirable that the system extracts this information implicitly. One possible solution is given by [22] to this problem is the usage of visual attention obtained through an eye-tracking device. In this, human preference is not measured through the rating system but through the way the user looks at different images, considering the eye fixation time and location.

—Many existing recommender systems use the collaborative filtering approach for their model. The famous cold start problem or the new item problem is a huge challenge in collaborative filtering. New items cannot be suggested until some users use them and the new consumers are highly unlikely to give recommendations due to the lack of ratings and purchase history as mentioned in. [9].

3. CONTENT-BASED FASHION RECOMMENDATION SYSTEMS

Content-based recommenders only use features of the garments as their driving force to recommend the valuable information to the consumers of the platform. Feature extraction from images is one of the essential tasks for e-shopping and online fashion stores recommendation systems, which are using these content-based recommenders.

The literature discusses various different ways ResNet-50 is used as one of the most widely used feature extractors, where resulting in one feature vector, having all the features of the single garment. [10] The following approaches are using feature extraction in different ways. Some are using Deep learning methods, ontology-based, fuzzy logic, K-means clustering, etc.

3.1 Fine-grained attribution model

Usually, the recommendation systems for outfits contain content-based information that considers texture, colour and style features. The limited set of features provide good recommendations but not always the most preferred ones.

Extracting incredibly intricate features from images of clothing can provide extraordinary results for the recommendation. For this purpose, rich details of clothes are taken into account using Deep Neural Network (AlexNet) and the consumers' personal features. [23]

Colour attributes from the images are extracted and divided into 64 category vector in the RGB histogram, along with styling attributes taken and segregated into 8 categories with further smaller texture and style sub-types.

Explicit user feedback is an integral part of the process. j -¿ attributes in each category. The value of the new preference after considering the feedback and the older preference is: [23]

$$p_{ij_{new}} = p_{ij}^*(1 + (\frac{1}{10j})^*k) \qquad (1)$$

i = 1,2..m and j = 1,2...n. Here, m = personal preference type of the user and n = attribute score in each type of preference of the user.

The recommendation model was finally given using the preferences which are personal to the user and detailed attributes: [23]

$$D = \sum_{i=1}^{6} k_i \sqrt{\sum_{j=1}^{n} (x_{ij} - p_{ij})^2} + k_v \sqrt{\sum_{l=1}^{6} 4(x_{vl} - p_{vl})^2} \qquad (2)$$

3.2 Occasion-oriented Fashion Recommendation

People like wearing appropriate clothes for different occasions. [12] The mixture of some fashion literature reviewed and novel approaches resulting in an occasion-driven fashion recommendation system is analysed in this paper.

User has a garment (used for pairing) and the occasion they want the recommendation for. Two primary criteria are considered to model this recommendation system. [12]

(1) Wear properly
(2) Wear Aesthetically

Human-body pose detection is also taken into account using 5 features from human-body parsing of the dataset's images. The wearing-properly aspect covers high-degree occasion attributes, and the wear aesthetically contains the low-degree feature attributes of the garments. [12]

To overcome the semantic differences posed by considering both of these attributes' categories,7 multi-value attributes of garments were taken into account. They are ranging from broad categories of types of the garment being recommended to detailed features like colour, texture, quality and design. These multi-value attributes were used as input variables for the input Support Vector Machine (SVM), creating recommendations including both the criteria (proper and aesthetic).[12]

3.3 An intelligent RS with Beauty E-expert via Latent SVM Based Model and Alpha blending

The paper tries to introduce a system called Magic Mirror which would consist mainly of two components Magic Closet which is an occasion-specific clothing recommendation system and Beauty E-expert that chooses hair and makeup through visual effects and datasets.

The paper aims to explore and build a clothing recommendation model through a unified latent Support Vector Machine (SVM) framework. It focuses on combining four components, namely, visual features vs attribute, visual features vs occasion, attribute vs occasion, attribute vs attribute, to develop the framework that satisfies the requirement of the customers. [20]

A part-based detection scheme is used to detect human parts and feature extraction. Features like histograms of oriented gradient(HOG), Local Binary Pattern(LBP), colour moment, colour histogram and skin descriptor. User's own clothing photos are taken and the most suitable clothing for an occasion is suggested through latent SVM. [20,13]. The attributes of lower and upper body clothes are denoted by vectors. The Beauty e-expert uses the Gibbs distribution for modelling the recommendation system. With the extracted beauty attributes, the final visual effects of hair and makeup are synthesized. Through Alpha blending of the test image I and hair, makeup template T, one obtains the result:

$$R = I * \alpha + (1-\alpha) * T \qquad (3)$$

3.4 Fashion recommender system using fuzzy logic for personalised garment design

A competent fashion recommendation system should be able to suggest garments and fashion design based on the body type, facial features and preferences of the user, whilst integrating them with the designer's knowledge and human perception. The fundamental structure of the fashion RS consists of three main functional components: inputs, learning data, and decision support unit. The learning unit stores the information of fashion professionals and consumers obtained from the sensory experiments. The decision support unit computes whether a certain fashion theme suits a particular body type. Inputs provide the user with an interface to interact with, consisting of body type, fashion theme and garment style to come up with recommendations. [21]

The system estimates the relevancy degree of the naked body ratios to the basic sensory descriptors. Using several fuzzy decision trees, the data is trained obtained through experiments. All the fuzzy rules are extracted for body shape and type, and descriptors are computed and accumulated for the fashion experts.

For normalisation of body ratios:

$$\delta_k = \sqrt{\sum_{l=1}^{p} br_{kl}^2} \qquad (4)$$

The coefficient δ_k is calculated from the learning data and $br's$ are the body ratios.

The relevancy degree for naked body shapes is calculated using the fuzzy-ID3 algorithm. The relevancy degrees are used to create a new garment design in accordance with the reference styles. The fuzzy relation between the style background and body type with the new clothing design is calculated and finally, the relevancy degree for body shapes with the garment is computed.

3.5 Fashion recommender using Text mining and Content Attributes

The researchers aim to provide an interactive platform to users with a mix-and-match technique for a particular clothing item. Currently, there are two branches of clothing recommendations, namely, mix-and-match clothing and similar clothing. The already

existing methods estimate the similarity of different clothing items and extract useful features from the clothing. Some work is also found on context-based personalized clothing recommendations. [16]

The researchers have used natural language processing techniques for extracting features and keywords of the clothing products and fashion items. Products are then regrouped and encoded to organise by fashion stylists and clothing experts. Two essential techniques, the nearest neighbour method and fuzzy similarities are combined in this proposed recommendation system. The product similarity is calculated by combining all features: [16]

$$Sim(C_i, C_j) = \frac{\sum_{i=1}^m w_i Sim(C_{f_i}, C_{f_j})}{\sum_{i=1}^m w_i} \qquad (5)$$

Where C_i and C_j are feature vectors, w_i is the weight of the ith feature, while $Sim(C_{f_i}, C_{f_j})$ is the similarity of the ith feature of clothing.
The authors have used a method to fine-tune and form a keywords list of each category. The results of the method prove that more than 95% of the products are correctly categorized.

3.6 Visual Information based recommendation system

Similarity scores across personal attributes of users and clothing features are calculated, unlike the similarity scores in the user-user database only. Two essential features of a robust content-based recommendation system are visual features comprising user information as well as product information. [2]

The user information and personal attributes are usually not considered necessary in conventional collaborative filtering techniques. A novel approach is taking the body height and gender of the user into account for an efficient content-based recommender system. *InceptionV3 (Google Net)* is used to predict the gender of the human.

The unique features from the garments are extracted using a CNN model, applied on *FashionAI* [2]. High detailing for garments was also performed by considering neckline design, pants length, sleeve length etc. For these, simple cloth parsing cannot give us the attributes. HSV values are taken, and then the division of the images into multiple small patches is performed to take into account these minute details. All patches will be then made into different pixel-wise K-means clustering to achieve better fine-tuning.

The similarity score is in this novel approach considered based on products and users, between database and clothing preferences of the user. Usually, it is only considered either between the users or the items, never between the cross-section of both.

$$S = \sum_i w_i f_i^n f_i^o \qquad (6)$$

4. COLLABORATIVE FILTERING FASHION RECOMMENDATION SYSTEMS

4.1 Advanced User-Based Collaborative Filtering

Conventional user-based collaborative filtering technique uses the user and their neighbour preferences' corresponding similarities to calculate the clothes' predictive scores. These approaches

are, however, inefficient as data is usually sparse, leading to irregularities. [25]

With widely increasing e-commerce businesses and e-shopping websites, they need to reach a more extensive audience base. Collaborative filtering is the day the most popular approach for recommendation models. A novel approach to make traditional user-based recommendations overcome their shortcomings of data scarcity and cold-start problems is to modify these systems and include better evaluation metrics. [16]

Advanced user-based collaborative filtering technique has efficient storage of user-item databases, saving valuable time for the consumers making the same amount of recommendation. The storage of User-Item data is not done in the form of a matrix; it's done in the form of a linked list, where the head is the value of the user, and the remaining nodes make up for the items. The node gets added to the linked list as the user buys one garment.

$$sim(v, u)_{CS} = cos(\vec{v}, \vec{u}) = \frac{\vec{v}.\vec{u}}{|\vec{v}||\vec{u}|} \qquad (7)$$

Two more improvements were made to achieve high standards than a traditional user-based CF technique. [25]

(1) The similarity between products is taken, not users. The following is the similarity between the items brought by user u, I_u and I_v:

$$sim(v, u)_{MCS} = \frac{|I_v \cap I_u|}{\sqrt{|I_v||I_u|}} \qquad (8)$$

Purchasing frequency gets improved.

$$sim(v, u)_{AUCF} = \frac{\sum_{|I_v \cap I_u|} \frac{1}{log(1+|U_j|)}}{\sqrt{|I_v||I_u|}} \qquad (9)$$

(2) Item Frequency factor: Decreases the impact of popular items and making the less popular items gain more popularity. U_j are the items purchased by both u and v.

4.2 Intelligent fashion RS using Multimedia mining and Soft Matting algorithm

In this paper, researchers aim to use fashion multimedia mining in the digital domain to construct the model. The fashion experts will be able to analyse the current trends in the fashion domain using multimedia information. The method would also be able to analyse the clothing and skin colour of the fashion model dynamically.

User data of clients is fetched using the library Coolchange. Interactive individual character is formed based on the client's attributes such as skin colour. An interlinked library is then created mapping the client's character and fashion clothing matching. A matching recommender gives the client an alternative as per their character analysis.

The filter allows correct input multimedia data so that fashion features are represented pictorially. The popularity of the input information or feature is checked. To seek multimedia information, the authors have used PageRank theory in order to find the association degree and analyze the web pages of multimedia.

The association degree is drawn by the following:

$$P(p_i) = \frac{d}{N} + (1-d)\left(\sum_{p_j \in Y(p_i)} \frac{P(p_j)}{M(p_j)} \right) \qquad (10)$$

D is the damping factor. p_1, p_2,p_3 are the pages in consideration; $Y(p_i)$ are the pages that link to pi; $M(p_j)$ are the number of outbound links; N is the total input pages. For segregating the foreground from the background effectively, localization is performed. It is done through optical characteristics of the surface of the input and the Horn/Schunck algorithm is used:

$$F(x, y, t) = F(x + d_x, y + d_y, t + d_t) \qquad (11)$$

$$M = \iint \left[(F_x u + F_y v + F_t) + a^2(|\Delta u|^2 + |\Delta v|^2) \right] dy \, dx \qquad (12)$$

Soft matting algorithm is applied to implement a refined contour of the fashion model organically.

$$(L + \theta T)C = \theta_{\tilde{C}} \qquad (13)$$

4.3 Functional Tensor Factorization Recommendation

The general idea of their approach is to recommend item sets instead of items to users. A functional tensor factorization method is proposed to model the interactions between the users and clothes. A gradient boosting method is employed to effectively utilize the multi-modal features of the items and learn nonlinear functions to map the feature vectors from the feature space into some low dimensional latent space.

Some challenges and issues will be explored, such as the cold start problem and incorporating social information from social networks to enhance performance.

N Categories of clothing items. U users. I(n) Set of n items. r_{u,O_t} - Rating score of Outfit t by user u.

r_{u,O_t} can be viewed as an entry in an $(N+1)^{th}$ order tensor. They decomposed this tensor so that unobserved entries in it can be predicted. In this problem, the tensors which can be observed are somehow extremely sparse. Due to practical reasons, a sound assumption can be made that every user can only rate a very small percentage of items. It would be difficult to learn effective high order interactions from such a limited number of observations. They, therefore, model r_{u,O_t} by factoring it into a set of pairwise interactions in some latent space.

Now gradient boosting is used to learn nonlinear functions to map the multi-modal feature vectors of the fashion items from the feature space into the latent space. This method is used to minimise the gradient of $\phi(h(x))$ with respect to h(x) and gradient descent is applied, i.e., compute the gradient of $\phi(h(x))$ with respect to h(x) at the current estimation $h_k(x)$ and form the next estimate as:

$$h_{k+1}(x) = h_k(x) - \alpha_k \nabla \Phi(h(x)) \qquad (14)$$

The computation cost for computing gradient g and terminal node coefficients are $O(P + L^n)$ and $O(P + L^n + Q)$ respectively.

4.4 Outfit Recommender system using RCNN and Multimedia web

The paper aims to propose a recommendation system to suggest clothing. The researchers have used Faster RCNN(Region-based Convolutional Neural Network) to implement the system which gives better average precision and faster object detection.[5]

For event identification, common objects are found at an event. Tags are allocated to each event and the finalised list of frequently occurring item is found by the equation:

$$argmax_{o_1,o_2,..,o_n} Sc(t_i) = \sum_{j=1}^{n} Sc(o_j) \qquad (15)$$

where Sc is the score of the subject.

All labelled training data is put in TFRecord file format for TensorFlow object detection. The model is trained to label all the data found for testing, training and evaluation. Finally, correlation is found between clothing and events in the form of a matrix and the most worn outfits are found using the Python Pandas library.

5. HYBRID FASHION RECOMMENDATION: OUTFIT RECOMMENDER SYSTEM

5.1 Bayesian Network Recommender System

Such systems work on predicting the items by analysing other users' behaviours and personal user choices. A Bayesian network is a system of joint probability demonstrating relations between user choices and situation. This approach recommends combination garments with the already given garment in our database. For instance, a suitable and preferred top for the jeans (already in your closet).

Occasion, temperature and season are used as context to predict the recommendation suitable to the user's needs. The user's history of garments and simultaneous feedback is produced to give the desired recommendation.

One can use a probability function to calculate colour and sleeve (attribute taken for garments). For colour, temperature and season are used, and for the sleeve, user history and occasion of the event is used. For the new colour node, the following probability function is used:

$$P(c) = \frac{F(c) \times PBay(c)}{\sum(F(c) \times PBay(c))} \qquad (16)$$

Where PBay(c) is the probability function for selecting the colour 'c', F(c) is defined by
If N(c) $\leq$ 3

$$F(c) = \frac{\sum N(c) - T(c)}{\sum T(c) + 1} \qquad (17)$$

To see how useful the function is, one can simultaneously take the user's feedback as a given priority. For garment P, the binary value will be calculated, taking the product of different properties of the garment. If this value is 1, then the product is recommended, and if 0, then it's not.

$$C(p) = Season(P) \times Occasion(P) \times Pattern(P) \times Color(P) \qquad (18)$$

The concluding recommendation call is made based on the user's evaluation feedback score. If the score is less than 3, the consumer can provide different parameter choices and recommend better outfits.

5.2 Recommender system based on User Ratings and K-means clustering

The authors of [9] propose a hybrid recommender system based on both user ratings and clothing attributes and features.

The clothing area from the input images is detected first from which the percentage of each colour is analysed. The item-rated matrix consists of the features of the product. Similar products are then found, and to obtain the recommended products through an extended rated matrix. The clothes are first clubbed and clustered into groups based on their internal attributes by using the soft clustering supported by fuzzy set theory. This is a modified and more efficient traditional K-means clustering algorithm. The probability of a single item can be calculated as :

$$Pro(j,k) = 1 - \frac{CS(j,k)}{MaxCS(i,k)} \qquad (19)$$

CS(j,k) is counter similarity between the object j and cluster k.

For extracting physical features from the model in the image, histograms of oriented gradients are used. This also distinguishes dominant colours from the selected area.

SVM techniques are used for human detection in input images. The profiles of models are extracted with maximum colour through colour extraction techniques. Colour extraction techniques are formulated to extract colours distinguishable by humans. The cloth vectors help calculate the final colour percentage in each input image, using the pixels in the image. For finalising a product for recommendation, collaborating filtering techniques are used for prediction by computing the weighted average of deviations from the neighbour.

5.3 Fashion recommender system with Hybrid collaborative filtering and fuzzy logic

The paper aims to come up with a user interface system and use technological tools to develop a recommender system that suggests suitable outfits and garments to the consumers. The system consists of a couple of databases. One dataset consists of a lot of fashion attributes and features. Another one consists of fashion goods and clothing items.[6]

The filtering consists of two important parts in the Personalised Recommendation System (PRS) model. The data from the web is first refined and filtered. Then the approach is taken forward by clustering the garments.

The features of garments are style, colour, quality, brand and material. These different features will be allotted one fuzzy set each A1 $\rightarrow$ style, A2 $\rightarrow$ brand, A3 $\rightarrow$ quality, A4 $\rightarrow$ material and so on. The function calculates the popularity of the items using fuzzy mathematical logic.

The data resource is selected and refined. Correlation is computed based on similarity. Formulae for correlation is the following:

$$sim(i,j) = \frac{\sum_{k \in I(i,j)} (r_{ik} - \bar{r}_i)(r_{jk} - \bar{r}_j)}{\sqrt{\sum_{k \in I(i,j)} (r_{jk} - \bar{r}_i)^2} \sqrt{\sum_{k \in I(i,j)} (r_{jk} - \bar{r}_j)^2}} \qquad (20)$$

where sim(i,j) is correlation , r(i,j) is User(i) and User(j) appraise elements of vector I(i,j) to produce r(i,j).
The recommendation is finally generated

$$\hat{P}_{u,k} = \hat{R}_u + \frac{\sum_{m=1}^{n} sim(\hat{u},m) \times (\hat{R}_{m,k} - \hat{R}_m)}{\sum_{m=1}^{n} sim(\hat{u},m)} \qquad (21)$$

In the recommender system, values are represented from large to small, making it possible to get n items from the first item to n-th item. The n items produce users recommendations set to top-N and these top-N are recommended to the user.

5.4 Garment recommendation system for Customized Garment

Paper proposed a robust hybrid recommendation model which makes use of the historical data of the customers of the company whose database one is using an analysis drawn from the user's profile and their eye tracking, mouse tracking, activities towards certain items, in the closet. [1]

The primary data attributes that one can have collected are customer's data, the pattern of buying apparels, customer assessment, apparels database and biometric data of the users. The nearest neighbour algorithm is utilized for Random forest classifier (RFC) is used to get a more accurate prediction of biometric parameters of customers.

6. ONTOLOGY-DRIVEN FASHION RECOMMENDATION SYSTEMS

6.1 Ontology-driven RS model based on collaborative filtering on the pre-processed input

Fashion ontology proved helpful in creating domain knowledge for recommendations for user's garments and clothing. Such a system will be beneficial in the fashion domain. The researchers have based their work on probabilistic reasoning schemes. The approach presented by the authors aims to provide users better interface experience and suggest clothing and fashion recommendations based on their feedback and choice. [14]

The ontology-driven framework consists of a user interface that uses the input images of garments and the user's face. The system recommends the best clothing that pairs up with the input and the visual personality of the user. The web-based system takes in the raw information, processes it, and is then used in the collaborative filtering algorithm. Recommendation Engine processes the input and makes recommendations based on attributes and features like colour, pattern etc.

Attributes:
Garment (top, bottom, overall) Body type (oval, normal figure, hourglass) Color (eye color, skin color, hair color) Occasion wear (party, office, casual, native) Season (summer, winter, spring and autumn)

Relationship:

"Is a", "Has" or "Feature of"

The body type attributes help us to make the Recommendation system completely personalized and not dependent on how the neighbour user(s) and their preferences are weighed.

6.2 Personalised Fashion Recommender system based on PServer Engine and Knowledge Integration

The aim of the paper is to present an ontology-based recommendation system that provides fashion advice and style preferences. After collecting the personal information from the user, the system would try to build a user model based on the user's body characteristics and facial features.[18]

The two main components of the system are (i) a knowledge repository or database and (ii) a general-purpose personalization server called PServer. Through the ontology-based recommendation system, the researchers were able to create an infrastructure for mass-customisation in the fashion domain under their work within the SERVIVE project.

For knowledge integration, Service Fashion Ontology integrates human and fashion features into one structured body of knowledge database. To get the information in a structured way, the authors have formed several classes, objects and data properties to structure the experts' knowledge.

Pserver Engine is a multi-purpose personalisation engine or web service which returns XML documents as results. It acts as a repository for individual models, which are automatically created when the user interacts with the system. The style advice rules are stored in the PServer by means of stereotypes. The elements of SFO(classes, subclasses) are mapped to elements of PServer(attributes and features).

7. EVALUATION METRICS

The quality of a recommender system can be decided on the result of evaluation. The type of metrics used depends on the type of CF applications. Metrics evaluating recommendation systems can be broadly classified into the following broad categories:

—Predictive accuracy metrics, such as Mean Absolute Error (MAE) and its variations.

—Classification accuracy metrics, such as precision, recall, F1-measure, and ROC sensitivity .

—Rank accuracy metrics, such as Pearson's product-moment correlation, Kendall's Tau, Mean Average Precision (MAP), half-life utility.

—Normalized distance-based performance metric (NDPM)

MAE is one of the most important and major Evaluation metric, used for 18 out of the 25 papers cited in this survey paper. Instead of classification accuracy or classification error, the most widely used metric in CF research literature is Mean Absolute Error (MAE), which computes the average of the absolute difference between the predictions and true ratings.

$$MAE = \frac{\sum_{(i,j)} |p_{i,j} - r_{i,j}|}{n} \qquad (22)$$

where n is the total number of ratings over all users, $p_{i,j}$ is the predicted rating for user i on item j, and $r_{i,j}$ is the actual rating.

The lower the MAE, the better the prediction. Normalized Mean Absolute Error (NMAE) normalizes MAE to express errors as percentages of full scale.

$$NMAE = \frac{MAE}{r_{max} - r_{min}} \qquad (23)$$

RMSE amplifies the contributions of the absolute errors between the predictions and the true values.

$$RMSE = \sqrt{\frac{1}{n} \sum_{(i,j)} (p_{i,j} - r_{i,j})^2} \qquad (24)$$

where r_max and r_min are the upper and lower bounds of the ratings and n is the total number of ratings over all users, $p_{i,j}$ is the predicted rating for user i on item j, and $r_{i,j}$ is the actual rating.

Precision and Recall are also used in multiple papers as an Evaluation Metric. They are used to generate F-Measure depicted as:

$$F_{Measure} = \frac{(a^2 + 1)Precision \times Recall}{a^2(Precision + Recall)} \qquad (25)$$

8. CONCLUSION

The growing expansion of e-commerce sites, technology and e-shopping fashion websites have called for an extensive need of Recommendation Systems [16]; they do save the energy and time that the users spend on finding the desired product.

Analysed how different challenges ranging from fundamental cold-start problems to non-inclusiveness of body-personal attributes of users are faced by the Fashion Recommendation Systems. There are solutions that were proposed in the paper as Deep-learning, CNN models for gender recognition and body height. [2] Ontology-based techniques were a completely novel, less researched domain where body type (oval, hourglass, pear) along with eye colour, body colour also taken as attributes to enhance the personalization. [14]

With extremely large database techniques like, Random Forest Classifier was used with 80000 images which outperformed SVM baseline with 41.38% vs 35.07% average accuracy on benchmark data. This proves to be one of the best models in the papers.[17]

Models like SVM, AlexNet and improvised CF techniques are used to provide state of the art efficiency with 82% modified, latent factor model 62% and 54% conventional CF model result accuracy. [24]

Problems by employing data-driven models to understand street fashion are solved by the dataset Fashion-136K. It is observed that data-driven models adapt well to the given domain of fashion as opposed to perceptually driven models that are very generic. [11]

The research literature is not in abundance but is good enough to form a survey that can analyse and explain every technique being used in the paper. Weighing the advantages and shortcoming of those.

The most widely used approach is content-based recommender systems since the features are the most essential factor for recommending fashion outfits, since users like the properties of clothes

and their choices being considered than their friend's choices. Collaborative Filtering techniques are most least likely to be used since they consider the preferences of other users and the style of fashion keeps changing with culture and society. Along with this, one can see how the efficiency of collaborative filtering techniques for fashion recommendation systems was the least, because of huge data sparsity and the non-likelihood of users not repeating their clothes, on various occasions. [8,12] The hybrid approaches used above to analyse and predict the recommendations by combining extensive collaborative filtering and content-based systems, which are more reliable and robust. [9] This mixture of approaches always works better since the disadvantages posed by both the techniques are balanced out. Future work has the potential to consider more Ontology-based techniques, increasing the effectiveness of collaborative filtering and carrying out more useful approaches for cloth parsing and feature extraction.

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