Big data in Fashion Industry

Divya Mahur [1] Nandit Pujara[2]

[1]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India
[2]Department of Computer Science and Engineering, Institute of Technology, Nirma University, Ahmedabad, Gujarat, India

November 2021

Abstract

In the world of fashion, big data plays an important part in trend forecasting, analyzing consumer behavior, preference and emotions. Any information related to a design item is consequently called style information which can be utilized for pattern investigation, client conduct examination, estimating, and so forth. Discovering and developing trends is the backbone of the fashion industry, and past statistics show that historical sales alone have been the determinant of trend popularity. But looking at historical sales is not sufficient, as nowadays, consumers increasingly expect and demand highly personalized shopping experiences. In this paper, an attempt is made to introduce the term fashion data and why it can be considered as big data. It also gives the classification of the types of fashion data by defining them briefly. Also, the methodology and working of a system that will use this data are briefly described in this paper.

Keywords - Big data, Digital Design model, Recommendation System, Virtual Fitting

1 Introduction

The design industry produces and makes different types of information and these loads of information come in different structures like images, words, and so forth. This information can be named Fashion big data as it depicts every one of the provisions of large information. Nowadays, the demands of the customer are constantly changing as they want garments with a personalized style, fit and pattern, color, print. Due to this reason, the fashion companies lose a lot of money due to excessive stock, which becomes obsolete because of changing trends. One of the solutions the industry came up with, for this problem was mass customization[1]. But, the problem with mass customization is that the customer is unaware of her/his needs and mostly lacks professional design knowledge. Due to this, most mass customized products are not as desired, and hence, the customer is rendered dissatisfied.

1.1 Fashion design based on big data

Fashion businesses gather data on sales from a variety of sources, stores, including websites, and mobile phone apps. They intelligently analyze the data and select diverse fashion-attribute data to identify color, fabric, style, brand, size, and other preferences among consumers based on age, gender, region, and other factors. This method serves as a guide for fashion designers and production managers. Fashion design can better meet market demands and brand characteristics in this way, while also greatly improving efficiency and quality.[2]

Fashion designers must apply data-mining results for a specific fashion to a specific type of design and judge whether it meets consumer needs based on the data when using big data. This can help to overcome traditional design's overemphasis on fashion designers' subjective aesthetics. Fashion designers can, for example, analyze the characteristics, patterns, styles, fabrics, and production processes of currently popular men's T-shirts when designing men's T-shirts. In this way, they can use big data platforms to identify the factors that customers care about the most when purchasing men's T-shirts, and then use those factors as design inspiration.

Quan et al. proposed a product innovation framework that combined Kansei engineering and deep learning to automatically transfer pattern, color, and other aspects of a style image to product shapes. Consumer preferences are obtained first, followed by the establishment of a BP mapping between semantics and product properties. Then, to transfer the style image to the content image and generate new products, a style transfer model is built. Finally, the semantics of the product are compared before and after transfer. The findings show that the new product image can retain not only the target product's shape but also the style image's characteristics. [2]

Figure 1: Product designs based on neural style transfer: (a) It is a content image, (b) Image of different styles, and (c) Resultant image

Figure 1(a) shows the content images, Figure 1(b) shows the style images, and Figure 1(c) shows the result images, using the female coat as an example (Figure 1). After processing, they input (a, b) into the style transfer model to get the desired results (c). The final product retains the shape of (a) while incorporating details such as colour and pattern that are similar to (a) (b). Despite the fact that this framework can automatically acquire new products without the need for manual intervention, the evaluation of style image is based on questionnaires rather than objective models, which introduces subjectivity into their framework. Furthermore, when using the framework to design fashion, the fashion style cannot be changed, and some design elements from previous fashions cannot be combined to create a new pattern, which is a major flaw in the framework. [2]

2 Related Work

Significant work has been done in the field of big data. Its significance and value has been proved in various sectors like healthcare, education, engineering, manufacturing, entertainment, retail. Currently, many organisations use big data technologies to their maximum advantage on a daily basis in order to extract value from them. In research, many authors have been pointing out the potential benefits of using big data as a new tool to understand everything from traffic jams to customer preferences, to deliver a more personalised experience. In the fashion industry, big data is still at an initial stage. Several fashion retailers are now making use of big data to understand their customers' behavior and to cater to their needs and meet their demands in a way that is beneficial to both.

2.1 Virtual customer fitting

Consumers can try on various styles or fashions in a virtual customer fitting system to better identify a fashion that suits their tastes and requirements. Customer satisfaction rises when products and preferences are more aligned, which may lead to increased willingness to pay. Customer manner can be subdivided into virtual customer fitting. [3]

2.1.1 Customer mannequin virtual fitting

A virtual mannequin of a customer based on 3D anthropometry tries on garments in customer mannequin virtual fitting. A manual avatar based on body measurement and a direct avatar based on a 3D body scan are the two methods for creating customer mannequins. Virtual-fitting systems for customer mannequins have a lot of advantages for both fashion companies and customers.

Song and Ashdown created custom pants for volunteers, who were then virtually tried on using a 3D body scan avatar. The virtual-fitting technology's overall accuracy was found to be sufficient for use. However, the technology wasn't perfect for visualizing fit; in particular, the 3D virtual model couldn't reflect the pants' silhouette. Ski jumping success is determined not only by technique but also by the skier's suit. Simona et al. created ski-jump suits in a virtual environment and compared them to real ones using two virtual body models (parametric and scanned). Virtual prototyping of ski-jump suits was done with Optitex software (Figure 2).

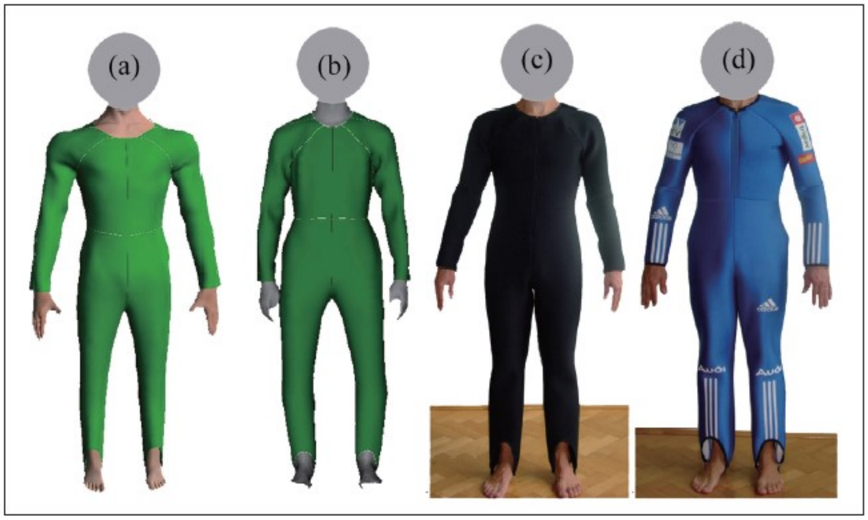

Figure 2: (a) Virtual prototype Ski-jump suits on parametric 3D body model, (b) virtual prototype on scanned 3D body model,(c) prototype of a ski-jump suit, and (d) professional ski-jump suit.

One of the most important factors influencing consumer purchasing decisions is fashion fit. As a result, no matter how good the fabric or how attractive the garment is, if it does not fit properly, the customer will not purchase it. Because consumers cannot physically try on garments when shopping online, estimating garment fit is a challenge.

To predict fashion fit, Liu et al. proposed a machine learning-based model. A parametric human model is used in this model for a specific customer to adjust to the real body dimensions (Figure 3(a) and (b)).

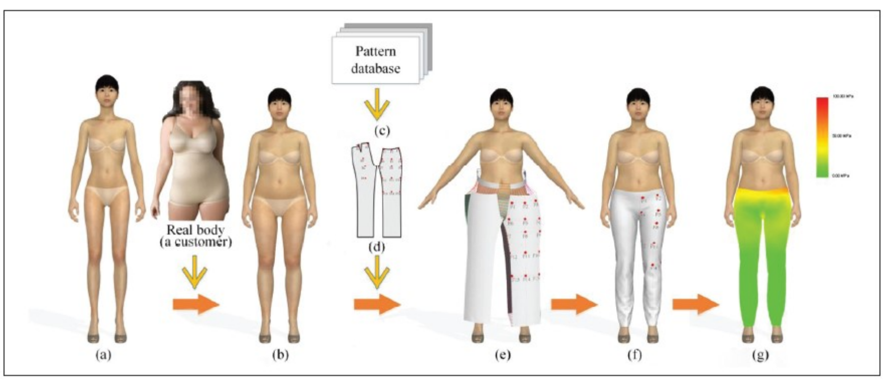

Figure 3: 3D human model adjustment and virtual try-on: (a) parametric human model, (b) adjusted human model, (c) search for patterns, (d) set measuring points, (e) arrange patterns, (f) virtual try-on, and (g) measure digital pressure.

Then, from a company database, fashion patterns are searched (Figure 3(c)). Then, on the selected patterns, several red points are marked to evaluate garment pressure at key points on the human body (Figure 3(d)). Then, using the adjusted digital human model (Figure 3(e)), a fashion is created and assembled to form a 3D virtual fashion (Figure 3(f)). Finally, pressures on the garments are simulated in predetermined positions (Figure 3(g)). Following these steps, the simulated garment pressures are added to the fashion-fit evaluation model to predict fit automatically. This proposed model can predict fashion fit automatically and quickly without the need for a real try-on, and it can be used to assess remote fashion fit in online shopping. This model, however, has some limitations which are not suitable

Gültepe and Gueduekbay created a virtual fitting room framework based on depth sensor data that could provide a realistic fitting experience with customized motion filters, body measurement, and physical simulation. With only 1 second of preprocessing time, this model creates a collision mesh and a physical simulation. Figure 4 shows six different clothing meshes, three for a male avatar and three for a female avatar. Because it only provides a realistic fitting experience for a standard human body type, this approach has the drawback of being insufficiently customizable. For example, the female avatar in Figure 4(b) has a very well-defined waist; in reality, a woman may have a larger overall body width.

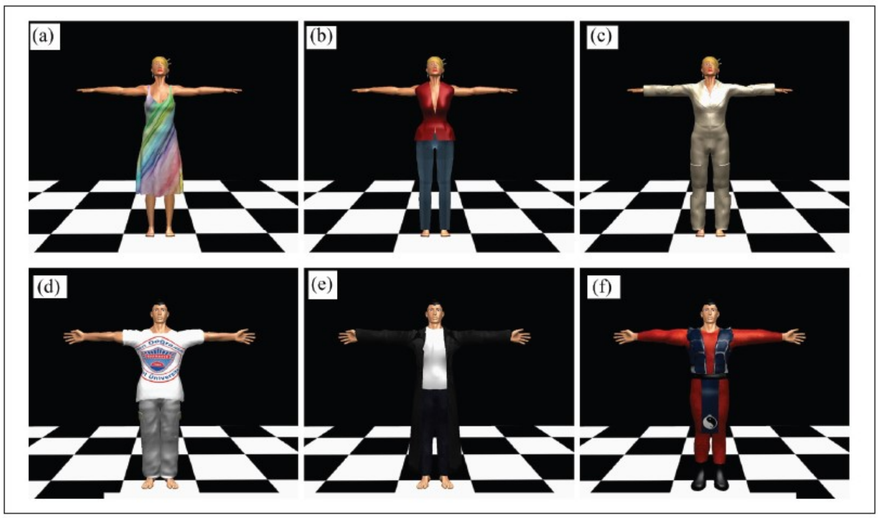

Figure 4: Designed apparel meshes for male and female avatars:35 (a), (b) and (c) are a female avatar with three different apparels, respectively; (d), (e) and (f) are a male avatar with three different apparels, respectively.

2.1.2 Real-human-body virtual fitting

Virtual fitting with a customer mannequin solves the problem of fitting without having to go to a store. Some customers, however, complain that the mannequins' faces aren't their own, making their virtual-fitting experience unsatisfactory and lacking in the sense of actually trying on the clothes. Some studies have attempted to solve this problem by developing real-human-body virtual-fitting systems.

Yamada et al.created an image-based real-human body virtual-fitting system to simulate fitting when shopping for clothes online. The system is depicted in Figure 5 as a whole. Whole Body images of a garment model and the customer are used as inputs to the system. First, both input images' body-contour models are estimated. The body-contour model of the garment model and the customer are then used to determine how the garment should be reshaped. After the customer adjusts his or her position in the composited garment image, a virtual-fitting image is generated. Finally, by adjusting the brightness of the customer image and retouching protrusions, a virtual-fitting result is obtained. The following are the benefits of this model:

1. The garment image is automatically reshaped based on the customer's body shape.

2. The brightness differences between the customer image and the garment image are automatically adjusted based on facial color.

3. Protrusions in the customer's cloth behind the garment are automatically retouched

One drawback of virtual fitting system is that it only accepts a 2D image of the garment, preventing the customer from seeing more realistic 3D fitting effects.

Bansidhar et al. proposed using Kinect to create a virtual dressing room. They developed a virtual fitting room framework based on a real-human-body model that can provide a realistic fitting experience through size adjustment, physical simulation, and customized motion filters. The dressing room is depicted in Figure 6. This model adjusts the avatar and calculates standard garment sizes based on the user's body measurements. It requires only one second of preprocessing to prepare the collision mesh and perform the human-body virtual fitting. This virtual fitting room eliminates the need for visual tags and can make fashion shopping faster, easier, and more accessible. It allows store owners to save money by reducing floor space and fitting rooms.

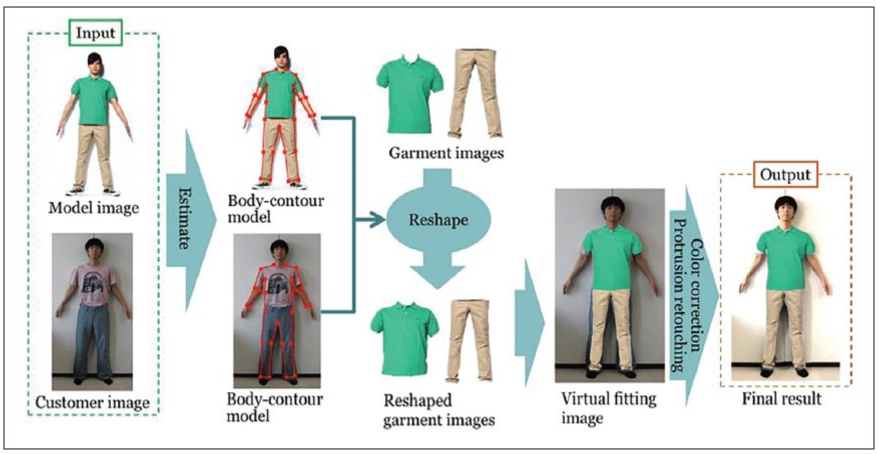

Figure 5: Image-based real-human-body virtual fitting.

It also cuts down on the time spent trying on different outfits and makes it easier to make good purchasing decisions. The dressing room is depicted in Figure 6. This model adjusts the avatar and calculates standard garment sizes based on the user's body measurements. It requires only one second of preprocessing to prepare the collision mesh and perform the human-body virtual fitting. This virtual fitting room eliminates the need for visual tags and can make fashion shopping faster, easier, and more accessible. It allows store owners to save money by reducing floor space and fitting rooms. It also cuts down on the time spent trying on different outfits and makes it easier to make good purchasing decisions. However, the Kinect has trouble reading small parts, and it lacks easy-to-use tools for the fashion design industry as a system with general 3D applications.

In this context, much of the research work has been done, to develop recommendation systems, which make use of the big data technologies to predict customer behavior and preferences. The primary function of a recommendation system, in general, is to predict what a customer would like to purchase, on the basis of their analyzed behavior, shopping preferences and the behavior of the people

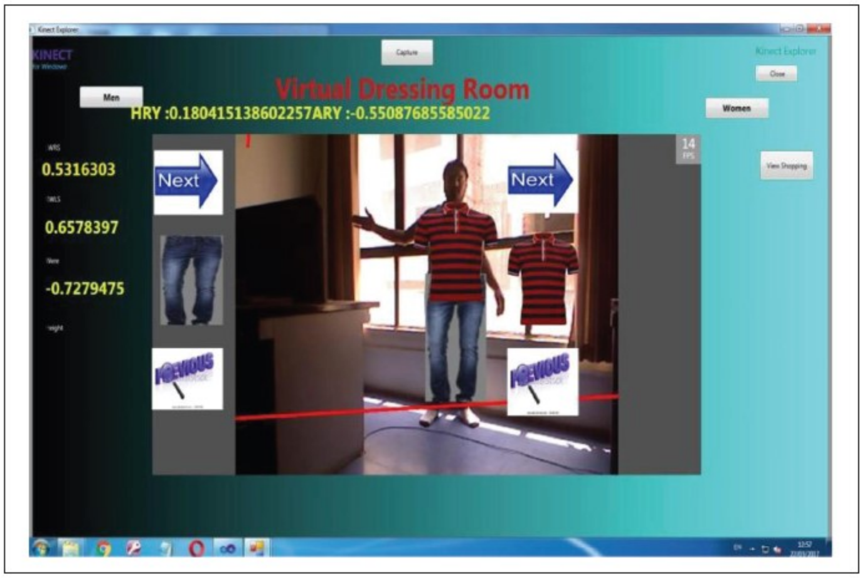

Figure 6: Virtual fitting room framework

with similar choices or demographics and most existing systems require sufficient information about the customer to be able to offer them products that will meet their needs.

Martinez proposed a recommender system that caters to the unavailability of enough information about customer preferences.[1] Their system collects information from the user by using numerical preference relation structure which only requires it to be filled with a small number of values.

McAuley proposed an image based recommendation system which modeled the human sense of the relationships between objects based on their appearance.[1] All these systems, however, require prior knowledge about the preferences of the customer. For this reason, many knowledge base recommender systems have been developed. Wang proposed a fashion recommender system that considers perception of both the fashion experts and the consumers.

2.2 Design-support systems for fashion

Snakes et al. created a "Mirror Mirror" system that allows users to design new fashions in front of a mirror and export design drawings to a printer. Regardless of design complexity or user skill level, Brodsky et al. aimed to eliminate time-consuming manual or computerized fashion conceptualization, pattern drafting, and 3D garment simulation. Their approach allows for custom product design, individual customized virtual fitting, and final garment preview on a figure using a cloud-based integrated environment (e.g. on a computer or mobile device). However, because the system records and saves 3D face models and fashion preferences, this system may pose a risk to personal information. As a result, increased network security measures may be required.

Mok et al. created a user-friendly fashion design system to assist customers in creating their preferred fashion. An interactive design model, a sketch representation, a composting method, and a user-friendly interface make up the system. The user interface design for the system is shown in Figure 8. All of the design elements are integrated into the design-support system, allowing customers to create their own fashions with ease. However, in this system, designs are presented as 2D sketches (Figure 8), which may not appear as appealing on 2D avatars as they do on 3D avatars.

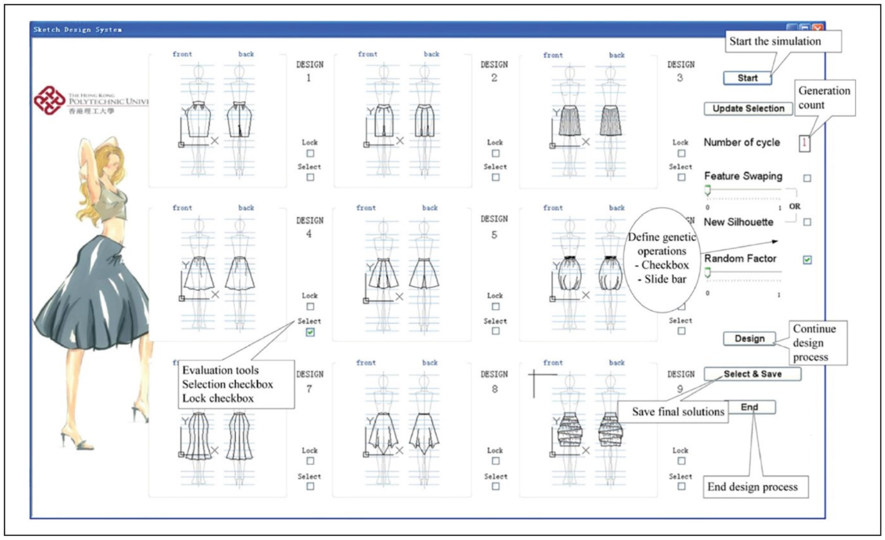

Figure 7: UI design of the design-support system

2.3 Fashion recommendation system

Customers' preferences for styles, colors, patterns, and other aspects are studied using online evaluations, search keywords, browsing behaviors, and purchase records on e-commerce platforms in one type of recommendation system. It then makes intelligent fashion recommendations based on the preferences of the customer.

Mok et al. created a user-friendly fashion design system to assist customers in creating their preferred fashion. An interactive design model, a sketch representation, a composting method, and a user-friendly interface make up the system. The user interface design for the system is shown in Figure 8. All of the design elements are integrated into the design-support system, allowing customers to create their own fashions with ease. However, in this system, designs are presented as 2D sketches (Figure 8), which may not appear as appealing on 2D avatars as they do on 3D avatars.

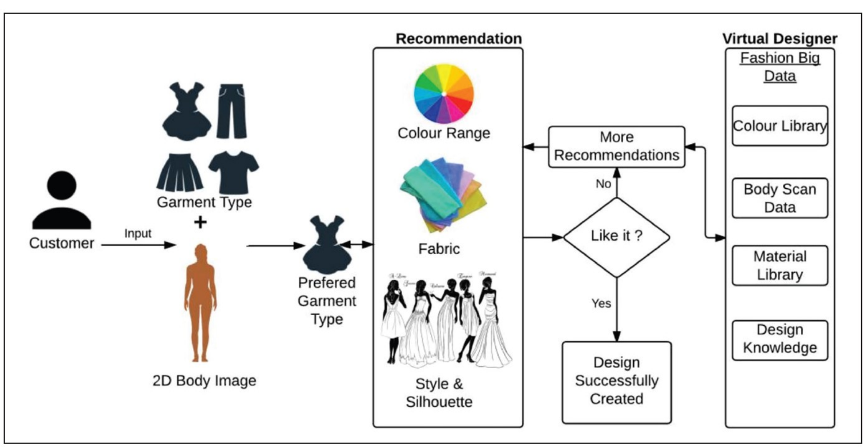

Figure 8: Fashion Recommendation System

Customers expect fashion design recommendation systems to not only recommend fashions that are similar to their current dress style but also to provide personalized style advice to help them better understand their own personal style.The recommendation system is depicted in Figure 9 as a whole. For fashion companies to increase their influence and profits, the intelligent recommendation is critical.

In reality, experienced designers can apply their design knowledge and previous successful design cases, as well as an understanding of the consumer's personality. As a result, developing designers' knowledge-based, personalised fashion recommendation systems is extremely important because they can effectively help consumers design fashion freely according to their own needs under the guidance of professional designers, which is conducive to increasing the success rate of fashion design. To assist apparel retailers in providing systematic expert recommendations, Dong et al.[2] developed an intelligent recommendation system. The system proposes an object-oriented blackboard and establishes expert rules based on apparel-specific characteristics. Based on a positive rule reasoning mechanism engine, the system generates personalized recommendations. [1]

As a result, from the perspective of a fashion expert, a human-machine interface is used to provide the customer with an apparel-matching solution. The results of the experiments showed that this system could recommend appropriate fashions for customers and improve their shopping experiences. Customers can codesign garments and communicate with experts, designers, and manufacturers using an e-customized codesigned system for fashion design proposed by Li and Chen. This system's main features include communicating, evaluating, and sharing design knowledge, as well as recommending styles to customers. This e-customized codesigned system improves on existing e-customized systems by providing fashion design recommendations, professional advice, and expert evaluation to consumers.

Year	Recommendation System Approach	Properties
Before 1992	Mafia, developed in 1990	• Content filtering. • Mail filtering agent for providing a cognitive intelligence-based service for document processing.
1992 to 1998	Tapestry, developed in 1992	• Collaborative filtering. • Developed by Palo Alto. • Allowed users only to rate messages as either good or bad product and service.
	Grouplens, first used in 1994	• Rate data to form the recommendation.
	Movielens, proposed in 1997	• Useful to construct a well-known dataset.
1999 to 2005	PLSA (Probabilistic Latent Semantic Analysis), proposed in 1999	• Developed by Thomas Hofmann. • Collaborative filtering.
2005 to 2009	Several Latent Factor Models such as Singular Value Decompositions (SVD), Robust Singular Value Decomposition (RSVD), Normalized Singular Value Deviation (NSVD).	• Collaborative filtering approach. • Find out factors from rating patterns.
2010 to onwards	Context-aware-based, instant-personalization-based	• Combined techniques of content and collaborative approach.

Figure 9: History of recommendation

3 Results

Our results with our first technique, model-based collaborative filtering, appear to be mixed at first glance. The testing set's RMSE is 0.0823, which is similar to a benchmark result from a different dataset in this research (with 20 million ratings). On the testing set, however, accuracy and NDCG (for the first 20 recommended items) for CF-ALS are 0.0003 percent and 0.0002 percent, respectively. On both of these metrics, our popularity model outperforms CF-ALS considerably. Finally, both models struggle to recommend the majority of the available pool of categories to users, as evidenced by catalogue coverage. Because accuracy-based measures are biassed in favour of popular items, our collaborative filtering strategy underperforms on precision and NDCG. CF-ALS offered more diverse recommendations on average than the popularity-based model, according to our catalogue coverage. However, because the great majority of categories are practically never evaluated (known as the long tail of things), CF-ALS has significantly lower accuracy, as it generates a wider range of but fewer relevant item recommendations (which might be more appealing than recommending the same popular categories).

One reason could be that the missing entries in our ratings interaction matrix (here unrated categories) are Missing Not At Random (MNAR): because users can select any category they wish, the probability of a missing rating is not random. As a result, the distribution of highest-rated category differs from the distribution of styles in the long tail (vast majority). It might be better to calculate accuracy metrics for the most popular styles and the remainder of the category collection separately.

Overall, according to the suggested styles to users in the given range the following results we got. Further work is under process to make it more precise and effective. Below are the graphs from the implementation of the system. The first one shows the frequency vs no. of ratings with a range of 20,000 rating per user and 250,000 frequency upper limit. Later one shows the distribution of number of users vs the ratings given to particular style and categories that is further used to predict and recommend the new styles to the particular user.

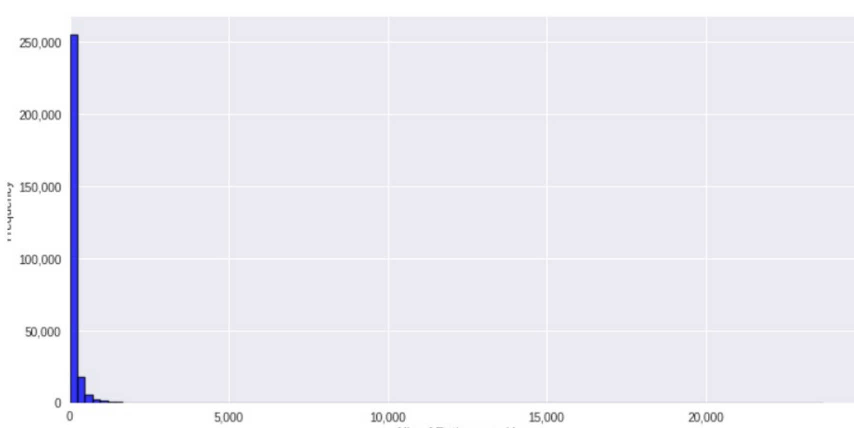

Figure 10: Frequency vs No. of ratings for the product

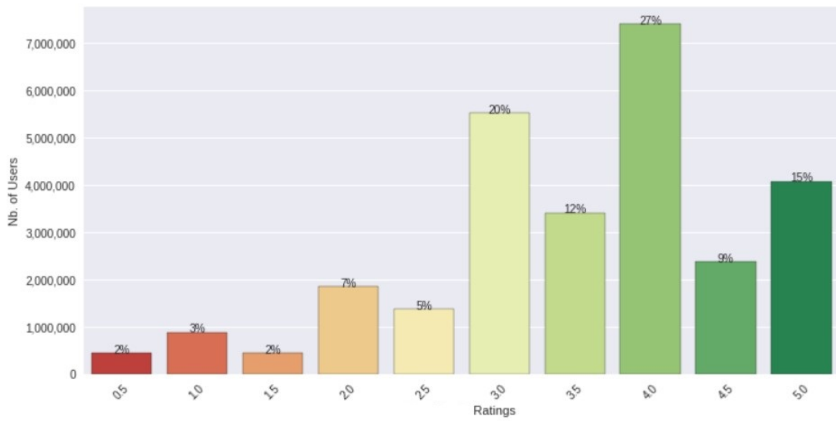

Figure 11: No. of users vs Ratings

4 Conclusion

Researchers, technology developers, retailers, and customers have all been drawn to the innovative use of big data and digital models in fashion design. In recent years, a variety of fashion design models have emerged. Market-driven fashion design models based on big data are currently the most popular. These gather consumer fashion needs, match tastes using a variety of methods (e.g., shopping websites, shopping apps, or market surveys), forecast fashion trends, and then design fashion using professional knowledge. [4]

A customer enters body size, selects fashion information (e.g. styles, colors, self-designed fashion), and then enters the virtual apparel display link as the main process of a design-support system. Customers can design their own fashion and create personalized designs using this model. Design-support systems, on the other hand, may cause issues because customers lack professional knowledge and are unable to always achieve the desired fashion effect, resulting in design failure. To address this issue, expert recommendation systems have been implemented, allowing fashion designers and even garment production departments to participate in consumer fashion design. Such systems can provide precise recommendations that are tailored to the individual needs of consumers, greatly increasing the success rate of fashion design. They may, however, raise the cost and time investment in customized design.

Fashion design platforms could be developed in the future that takes into account not only appearance but also comfort and functionality. Consumers can work with experts on fashion design and virtual try-on, as well as view comfort parameters after trying on apparel in real-time, to get the best dressing experience possible.

References

[1] S. Jain, J. Bruniaux, X. Zeng, and P. Bruniaux, "Big data in fashion industry," *IOP Conference Series: Materials Science and Engineering*, vol. 254, p. 152005, 10 2017.

[2] L. Zhao, S. Liu, and X. Zhao, "Big data and digital design models for fashion design," *Journal of Engineered Fibers and Fabrics*, vol. 16, p. 155892502110190, 01 2021.

[3] A. Fiore, S.-E. Lee, and G. Kunz, "Individual differences, motivations, and willingness to use a mass customization option for fashion products," *European Journal of Marketing*, vol. 38, pp. 835–849, 07 2004.

[4] C. Remondino and C. Marino, "Fashion industry as a big data enterprise for sustainability," *Current Trends in Fashion Technology Textile Engineering*, vol. 3, 03 2018.