FashionSys: End to End Fashion Recommendation System (G17)

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ABSTRACT

Fashion, a thriving global industry worth billions of dollars, intricately influences our daily lives by serving as a means of self-expression and societal interaction. However, despite substantial progress in machine learning (ML), automated outfit recommendations remain challenging due to the intricate blend of human creativity, style knowledge, and individual expression necessary to transform disparate clothing pieces into a unified ensemble. Some existing tools and systems have attempted to tackle this problem; however, they necessitate users to meticulously document their entire wardrobe, impeding user experience due to the time-consuming nature of this task. In this paper, we introduce FashionSys, an end-to-end personalized fashion recommendation system utilizing computer vision models to infer user style and generate outfit recommendations. Our system is designed for consumers who start outfit creation with a single focal piece of clothing. By offering real-time recommendations that construct an outfit around this item, our lightweight system eliminates the need for users to digitize their entire wardrobe, enhancing the user experience.

1 INTRODUCTION

Fashion has played an integral role in human history, evolving from the practicality of animal skins to a thriving multi-billion-dollar industry that shapes our daily lives. Today, fashion serves as a creative outlet for individuals to express their identities and influences societal perceptions. From our clothing choices to the impressions we form about others, fashion continues to impact societal dynamics, maintaining its significance throughout human civilization.

Advances in ML applied to fashion are changing how people interact with clothing. Amazon's Echo Look allows users to rate their outfits through selfies [22], while Intel's Magic Mirror enables virtual clothing trials [21]. Companies like Stitch Fix use data-driven models to curate personalized clothing selections [23].

Several tools such as Acloset, Stylebook, and IndyX leverage ML algorithms to suggest outfits [11, 15, 16]. However, these platforms require users to document their entire wardrobe, a process known to consume substantial time—often spanning multiple hours [18], dissuading full engagement due to the time-consuming nature of this task [18].

To design the future of personal fashion, we look to solving the age-old question that is the bane of many peoples' mornings: What do I wear right now?

Navigating this challenge entails moving beyond merely assembling pre-existing clothing items and delving into understanding individual stylization preferences.

In this paper, we introduce *FashionSys*, a scalable personalized end-to-end Fashion Recommendation System. Drawing inspiration from *The Elements of Fashion Style* by Kumar et al. [26], we aim to infer high-level styles from low-level elements. The typical user begins by uploading a picture of a single piece of clothing they wish to showcase in their outfit. The system then infers the style and provides real-time recommendations to complete an outfit that matches the inferred style.

This system builds upon existing works in the domain of ML applied to fashion. We integrate techniques from the distributed systems domain to ensure scalability to accommodate a large number of users. The system design and ideal user interaction is broken down as follows:

1.1 System Design

- *Frontend:* Web application where users upload images of clothing.
- *Backend:* Hosting API server for models, databases of Polyvore outfit embeddings and personalized outfits.
- *Models:* Pre-trained fashion computer vision classification model [6], real-time filtering model based on user style input, and real-time streaming ML ranking model based on user preferences.

1.2 User Interaction Flow

(1) User uploads images of clothing pieces they would like to wear. Previous user information, responses to recommendations, time of day, and weather are also included.
(2) Computer vision classification model identifies the article(s) of clothing, specifically the design elements (color, material, silhouette, trim) [26] and uses these as inputs to the recommendation model.
(3) The recommendation model matches design elements with possible outfits in the database by comparing learned type-aware embeddings [19].
(4) Ranking model outputs the top n outfits to the user based on preference filtering etc.
(5) User decide whether to accept the recommendation or not, which will be used prompt the next recommendation in real-time.

2 RELATED WORK

2.1 Synopsis of Recommendation Systems

In recent years, Recommendation Systems (RS) have become crucial elements of e-commerce platforms, transforming how users explore products and services. By analyzing user behavior and preferences, RS addresses the information overload on the internet [12], providing tailored recommendations aligned with users' interests and needs. These systems have evolved, integrating advanced algorithms to deliver personalized suggestions [12]. In this section, we review RS, covering key phases such as information collection, learning, and recommendation [3].

The information collection phase is pivotal for RS as it marks the beginning of learning about a user's preferences, a crucial step in constructing accurate predictions. In the context of fashion RS, this phase is particularly essential for understanding a user's style preferences. By comprehensively gathering data on a user's interactions and feedback, RS can effectively tailor recommendations to suit individual tastes and needs, thereby enhancing user satisfaction and engagement [7]. Therefore, it is imperative for the system to consider user preferences in its decision-making process.

Failure to do so may deter users from utilizing FashionSys or any other recommendation system, as it would offer generic recommendations without personalization. Users expect RS to provide tailored suggestions that resonate with their unique fashion preferences and style choices. A one-size-fits-all approach would render the system indistinguishable from basic recommender systems, failing to meet the evolving expectations of today's discerning consumers [9]. Thus, to truly capture user interest and loyalty, RS must prioritize personalization and adaptability, ensuring that every recommendation reflects the individuality of each user.

The process of learning a user's preferences can be approached through both implicit and explicit methods. Explicit feedback, which involves direct input from users, provides targeted information to the Recommendation System (RS) while fostering transparency and user trust in the system [14]. In the fashion industry, this often involves pre-surveys of personal tastes or feedback on proposed outfits by the RS.

On the other hand, implicit feedback plays a crucial role in analyzing user behavior to glean preferences [2]. In the context of fashion, this might include analyzing clothing uploaded by the user. For FashionSys, our focus will primarily be on explicit feedback to streamline the user experience and minimize the burden of uploading clothing items. Nonetheless, we will integrate implicit feedback into the process by examining users' recent outfit trends and analyzing the clothing pieces they frequently utilize. While implicit feedback will be hard to collect by nature, this approach allows us to strike a balance between user convenience and system effectiveness.

The Learning Phase is where information reduction occurs, enabling the system to focus on specific fields and filter out extraneous noise from the vast amount of information [7]. This process aids in eliminating outfits that may not align with a user's preferences. For example, it can assist one user seeking a casual comfort style and another user aiming for a Bohemian feel by excluding Grunge styles. This phase is essential for simplifying the exploration zone on behalf of the user. FashionSys will analyze the style embeddings of clothing to efficiently filter out unwanted items.

The Recommendation Phase is the subsequent step, wherein the system returns items that the user would find desirable. Recommendations are typically sourced from pre-existing datasets or information collected from the user, though in our case, it will primarily rely on existing databases [12]. Moreover, they are frequently accompanied by a rating or feedback component, enabling users to evaluate the RS results [27]. This involves determining whether an outfit or piece of clothing is suitable for the user's preferences.

2.2 Typology of Fashion Recommendation Systems

When it comes to RS in the Fashion Industry, they can generally be categorized into five different categories: fashion image retrieval, person wardrobe RS, fashion pairing RS, smart recommendation, and social-network-based recommendation [3]. Fashion image retrieval systems [13, 20] assist users in finding similar clothing items based on image queries, employing visual features such as color, pattern, and style to recommend visually analogous items. Conversely, person wardrobe recommendation systems [1, 8] analyze a user's existing wardrobe, suggesting new items that complement their current clothing. Fashion pairing recommendation systems [5, 10, 25] take a different approach by recommending complete outfits, suggesting complementary pieces for specific items like tops or pants. In contrast, smart recommendation systems [17] go beyond user preferences and item features, incorporating contextual information such as weather, occasion, and user behavior to recommend suitable clothing options. Lastly, social-network-based recommendation systems [24, 28] leverage social connections to personalize recommendations, analyzing user interactions within social networks to suggest items based on the preferences of friends or influencers they follow, thus tapping into trends and styles within their social circles.

FashionSys prioritizes the utilization of a Fashion Pairing RS, emphasizing the completion of outfits over finding similar items. This approach aims to streamline the user experience by minimizing the time required for users to upload their entire wardrobe. Additionally, we intend to incorporate Smart Recommendation features, leveraging contextual information to enhance the relevance of recommendations. While Social-Network Based Recommendation is a future goal, we recognize its potential to identify trendy styles and style-adjacent outfits for users [4].

3 TIMELINE

(1) 2/25-3/03: Environmental Setup: Acquire machines, download required technologies, and upload Kaggle Polyvore dataset to multiple machines
(2) 3/03-03/17: Build Basic Recommendation System: Integrate computer vision for clothing identification, train model for basic top/bottom pair recommendations
(3) 03/17-04/14: Experiment with ML models (e.g., Random Forest, NN) to incorporate User Features and real-time personalized feedback, Develop Ranking Model
(4) 04/14-04/28: Develop front-end for multiple user inputs and full outfit creation
(5) 04/28-05/05: - Optimize with LLM for user input, enhance decision explainability, Prepare demo and report

4 BUSINESS PLAN

There is no doubt that your appearance is important to the way the world perceives you and the way you perceive yourself. To establish credibility, many professions require their employees to dress in a business professional attire. For some, wearing preferential attire brings to the surface a sense of confidence and individuality. The outfits they wear are strong modes of self-expression and personality. We hope to bring this sense of confidence and individuality to everyone. Our goal is to create a fashion recommendation system for users to input what pieces of clothing they would like to wear and we will provide them with recommendations of possible outfits they can create with these pieces suited to their learned personalized preferences.

Currently, there are no **free** personalized fashion recommendation applications. For a source of revenue, we plan to collect user data while abiding to privacy and security requirements and plan to host ads on our platform. Users can have the option of removing ads for the price of 0.99 per month. With this application, users will not only save time choosing the best outfit for them but will be able to feel like themselves using the personalized recommendations provided by the application.

To address costs, the initial product will be created using open source models and data. For compute and serving, we plan to begin with a local web-based application and develop a plan for scaling the application if preferably viewed by users in the future.

In addition, for future work, users can compare their fashion recommendations with their peers and explore new styles that celebrities and their peers like on the application. The application will begin as an initial prototype for recommendation but the eventual goal is to turn it into a mode of social media that is used collaboratively amongst users to express their creativity and passions for fashion.

We envision conducting user studies to gain insights into user preferences and refine our recommendations accordingly. Understanding what users find most fitting and exploring revenue options that align with user preferences will be pivotal. As our platform is designed with the user in mind, we aim to offer revenue options that enhance the user experience. Additionally, we plan to explore revenue streams beyond ad-based models, seeking input from users to determine the most preferable options. Through user studies and feedback, we will continue to evolve our platform to better serve the needs and desires of our users.

Afterall, as HOF NFL player and fashion icon Deion Sanders said "If you look good -> you feel good, if you feel good -> you play good, if you play good -> "they" pay good -> you eat good, sleep good, look good.

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