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A Real-time Hybrid Clothing Recommender System: Integrating Content-Based Learning with User Interaction

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Abstract:

A real-time hybrid recommender system for clothes is shown in this work. It uses a swipe-based interface in which users indicate their preferences by making simple gestures: left swipes for products they dislike and right swipes for items they like. This user-friendly interaction model improves usability and engagement by collecting user feedback with simplicity. In order to generate comprehensive item profiles, the system analyzes important garment qualities like color, pattern, material, design, and style using a combination of content-based and collaborative filtering algorithms. These profiles aid in the recommendation model's efficient comprehension of user preferences. Concurrently, the model incorporates user interactions, creating an adaptive loop that continuously improves suggestions. The system is guaranteed to remain sensitive to changing preferences because to its dynamic feedback mechanism, which provides tailored suggestions that closely match each user's preferred style.

This hybrid strategy provides a scalable, responsive answer to issues like the cold start problem and low user engagement. Initial recommendations for new users are made possible by content features, and accuracy is gradually increased through ongoing learning from user interactions. By tailoring recommendations to each user's preferences, this strategy not only increases user satisfaction and engagement but also increases conversion rates. The system also gives retailers useful information about consumer preferences and fashion trends, enabling them to make data-driven choices about marketing and inventories. All things considered, this recommender system is a potent instrument for the fashion sector, combining accuracy, versatility, and easy usability to provide incredibly customized experiences.

Keywords:

Collaborative Filtering, Content-Based Filtering, Hybrid Recommender System, Deep Learning, Machine Learning, Hybrid Clothing Recommender System, Similarity Measures, Item-User Matrix, Neural Networks, Dimensionality Reduction, Cold Start Problem, UserItem Interaction.

Introduction:

These days, online clothing sales have grown in popularity and appeal due to their affordability and high quality. Yintai.com, Vancl.com, and Shop.vipshop.com are a few instances of these prosperous websites that offer hundreds of clothing items to online buyers. Online buyers face the difficulty of selecting a quality product from a wide range of possibilities. To make buying easier, we present a collaborative clothing recommender in this post. This system's capacity to suggest apparel based on both user ratings and clothing qualities is one of its distinctive features. Our simulation environment's experiments demonstrate that the suggested recommender can more effectively meet user needs. 【2:1】

Introduced in the mid-1990s, recommender systems are crucial e-commerce platforms that make product recommendations based on user behavior. They play a big part in increasing revenue, improving cross-selling prospects, and cultivating customer loyalty in addition to helping consumers find suitable goods. These systems can be broadly classified into three types: collaborative, which leverages the preferences of comparable users; content-based, which depends on product qualities; and hybrid, which combines the two methods. This article introduces a hybrid recommender system made especially for clothes purchasing, which makes use of both product qualities and customer ratings to provide more individualized and fulfilling suggestions. 【2:2】

These days, recommender systems are a necessary component of our lives. Recommender systems are used by the majority of social websites to improve user experience. A recommender is very important because clothing is one of the most popular domains on online buying platforms like Amazon. Retrieving goods based on user preference—that is, resemblance to the user's prior purchases—was a common focus of earlier recommender systems. But in the clothing industry, recommendations also depend on how well the prospective items fit the ones that have already been bought. For instance, if a customer has recently bought a shirt, he or she might wish to buy a new pair of jeans instead of suit pants. Such matched partnerships are equally common in other areas of life. Our goal in this study is to suggest new clothing that will better fit the user's existing wardrobe. This novel recommendation approach would enhance the existing recommendation literature and perform better in the clothing sector. Experiment results show that our method can lead to better recommendation performance in the Clothing domain.【4:1】

Recommendation systems are crucial in today's digital world, especially when it comes to online shopping, where they improve user experience by making product recommendations based on past purchases. In addition to customisation, they increase company value by drawing in new clients. Considering how prevalent fashion is in e-commerce, clothing recommendations are particularly crucial. Conventional systems mostly consider user preferences and frequently promote related products, such as jeans if a user has already bought them. Nevertheless, these systems frequently fail to consider whether newly purchased products correspond with previous purchases, which may result in underutilized items. This essay discusses the significance of matching new clothing with previously purchased items while taking color, texture, and style into account. Users want clothes that go well with their outfits, therefore compatibility is important. The suggested approach blends matching strength and user preferences to make better suggestions.【4:2】

By effectively managing complicated data, deep learning plays a critical role in improving recommender systems, which seek to provide suggestions based on user preferences. Recommendation algorithms are being used more and more by online shopping platforms, particularly in the apparel industry, to increase sales. This tendency has been driven by the COVID-19 pandemic-related shift to online activities. This study introduces a deep neural network-based content-based apparel recommender system that automatically generates product attributes, such as category and gender, obviating the requirement for manual feature extraction. The method provides fresh, pertinent, and surprising suggestions while resolving the cold start issue for new goods. Even without taking demographic information like gender

into account, experimental results show that it performs better than comparable models by attaining a lower loss. 【5:1】

In a variety of industries, including e-commerce, music, and film, recommender systems are crucial tools that let customers locate pertinent products fast and effectively. There are four primary groups into which these systems fall. When new users or things lack data, Collaborative Filtering (CFRS) faces the cold start issue. CFRS makes suggestions for items based on similar user behavior. Although they too have the cold start problem, content-based systems (CBRS) suggest products that are comparable to those a consumer has already dealt with. Knowledge-Based Recommenders avoid the cold start issue by employing user-defined preferences to cater to specific commodities, like cars or apartments. Multiple strategies are combined in hybrid systems to improve accuracy and dependability. 【5:2】

Fast fashion and the growth of e-commerce are the main drivers of the fashion and textile industries' explosive growth, according to the study. By providing personalized recommendations amidst the plethora of online options, a successful fashion recommendation system is crucial to enhancing the user experience. FRSs analyze user preferences and forecast fashion trends by leveraging advances in image processing and computer learning.【7:2】
Despite FRSs' potential, there isn't a thorough analysis of the academic literature that incorporates cutting-edge models and methodologies. By thoroughly examining the main models, filtering strategies, and assessment criteria employed in the creation of FRS, this research seeks to close that gap. Researchers and practitioners can learn more about the advantages and disadvantages of current systems from the review.【7:2-3】
The writers stress how the popularity of internet buying and growing living standards have made fashion more significant in daily life. Conventional recommender systems sometimes overlook consumers' visual preferences because they are based on past purchases.【7:1】

This disparity drives the creation of image-based fashion recommendation systems that provide visually comparable products to increase customer satisfaction. This study suggests a customized fashion suggestion system utilizing image-based neural networks in light of the difficulties customers encounter when choosing clothing online. In contrast to traditional approaches, the suggested system makes recommendations based on product photos, satisfying customers' desire for aesthetically pleasing fashion goods.【9:2】

Literature Survey:

The idea of hybrid recommendation systems designed especially for the online apparel retail sector is presented in the work by Hu et al. The dual requirement of making product recommendations based on item qualities and user preferences is met by this system. Conventional recommender systems, which usually utilize content-based approaches or collaborative filtering, sometimes fail when item features are not fully captured or when consumers do not have long interaction histories. Hu et al.'s hybrid model offers a more thorough recommendation framework by combining various strategies to address drawbacks like the cold-start issue. This is especially important in online buying settings because customers require individualized direction due to the abundance of possibilities.【2:1-2】

In order to identify garment traits like prominent colors, the HCRS system architecture is organized around a multi-stage process that starts with human detection and image preprocessing. Traditional collaborative filtering techniques are enhanced by an enlarged item-rating matrix that incorporates these qualities. HCRS is a modified K-means clustering technique that incorporates fuzzy set theory, which allows things to belong to many clusters at the same time, in contrast to traditional matrix-based recommenders. A more accurate and customized suggestion output is made possible by this, which allows for a nuanced representation of user preferences and item features.【2:3-4】
Hu et al. focus on measures like Mean Absolute Error (MAE) in their extended trials utilizing a dataset created from 163 individuals and 50 apparel items. The findings show that, in comparison to conventional collaborative filtering methods, HCRS dramatically lowers prediction error. Furthermore, a richer user experience is offered by the system's capacity to incorporate both textual and visual elements into its recommendation engine. The results indicate that by providing more context-aware and targeted product recommendations, this hybrid strategy not only improves user satisfaction but may also have implications for raising online sales conversion rates.【2:5-6】

The study by Gharaei et al. is set in the backdrop of quickly expanding online retail platforms where the volume of data makes human feature extraction for product recommendations unfeasible. The study highlights that the cold-start problem, which occurs when there is inadequate user-item interaction history, frequently causes traditional collaborative filtering techniques to fail. To get around this, the authors suggest a content-based approach that uses deep neural networks (DNNs) to automatically extract features from product photos. This improves scalability and does away with the requirement for human input. 【4:1-2】

A deep convolutional neural network (CNN) that can handle feature extraction and classification tasks concurrently forms the basis of the suggested system. For binary classification problems like gender detection, this design consists of 13 layers with ReLU activation functions, followed by a final sigmoid layer. To reduce errors, the network is trained by combining the Nadam optimization method with category focal loss. Furthermore, the system makes use of transfer learning by optimizing previously trained models to improve performance on particular tasks, such as gender recognition and apparel category classification. 【4:4-5】

Results from experiments show a significant increase in prediction accuracy and suggestion precision. With a precision rate of 73.7%, the system outperforms baseline models like ResNet-50 in terms of training efficiency and loss reduction. Furthermore, the system efficiently suggests new and surprising items by utilizing cosine similarity to assess the proximity of feature vectors, which raises user happiness and engagement. This illustrates the system's usefulness in actual e-commerce platforms where customer retention depends on prompt and precise recommendations. 【4:6-7】

Lei et al. investigate a new method for making clothing suggestions by emphasizing how well freshly suggested goods match ones that have already been bought. This approach takes into account visual and contextual characteristics including color, texture, and shape, in contrast to conventional systems that rank user preferences only on the basis of past purchases. The study addresses a critical gap in current recommender systems, which often overlook the importance of item compatibility in fashion, where matching aesthetics play a crucial role in user satisfaction 【5:2-3】

The approach integrates visual features through hierarchical clustering and uses a time-enhanced version of SVD++ to record changing user preferences. This hybrid methodology evaluates the visual compatibility of new suggestions with already-owned wardrobe items in addition to tracking changes in user preferences over time. By grouping previously bought products according to their visual and contextual characteristics, the method lowers computing complexity and improves item matching accuracy. 【5:4-5】

This study offers a thorough analysis of fashion recommendation systems (FRS), outlining their importance in improving customers' individualized purchasing experiences. By selecting pertinent products according to user preferences, the authors highlight their function in mitigating information overload as they examine the development of FRS, namely in the e-commerce industry. To illustrate the complexity of consumer behavior, a number of elements that impact fashion choices are analyzed, including demography, location, and social environment. 【7:2】

The review divides FRS into several categories, including hybrid approaches, content-based filtering, and collaborative filtering. The authors describe cutting-edge methods such as recurrent neural networks (RNNs) and convolutional neural networks (CNNs), demonstrating how they are used to extract textual and visual characteristics from fashion items. By examining both explicit and implicit user feedback, these methods help to improve theaccuracy. 【7:8】

The authors list a number of issues with the present FRS, such as the requirement for real-time processing, cold-start issues, and data sparsity. To increase system resilience, they suggest incorporating social media data and investigating hybrid methods. To improve personalization, future studies could concentrate on improving deep learning algorithms and adding user-generated information. The article ends by providing recommendations for creating FRS models that are more successful based on the knowledge gained from their review. 【7:32】

This article uses image-based neural networks to tackle the problem of tailored fashion recommendations. This method concentrates on visual characteristics taken from input photographs, as opposed to conventional systems that

leverage user purchasing history. By creating recommendations that closely correspond with each user's personal aesthetic tastes, the authors hope to improve the user experience. 【9:1】
In their study of current recommender systems, the authors draw attention to their limited visual analysis and reliance on textual data. They talk about earlier attempts to use convolutional neural networks (CNNs) to integrate visual features, but they point out that there aren't any complete solutions that combine visual similarities with tailored recommendations【9:2】.Their suggested system, which employs a nearest-neighbor strategy supported by deep learning models, was developed in response to this gap. 【9:3】

Methodologies:

E-commerce sites provided the dataset for HCRS, which was gathered with an emphasis on product attributes and user reviews. The item-rating matrix and the group-rating matrix are the two sorts of matrices that are constructed in order to build the system. While the group-rating matrix depicts item groups based on common product attributes like color, texture, and style, the item-rating matrix records user interactions in the form of specific ratings. The authors used a fuzzy K-means algorithm to improve their clustering mechanism in order to solve the sparsity problem that frequently arises in collaborative filtering systems. This approach improves the representation of overlapping item qualities and user preferences by enabling soft clustering, in contrast to normal K-means, where an item can belong to numerous groups. 【2:3-4】
HCRS incorporates a complex visual analysis pipeline that uses color extraction and histogram-based approaches to increase recommendation accuracy. Support Vector Machines (SVMs) for object categorization in conjunction with Histogram of Oriented Gradients (HOG) are used for human detection on garment photos. Dominant colors are retrieved and quantified into vector representations when the garment region has been identified. By including these vectors as pseudo-ratings into the group-rating matrix, low-level visual input is efficiently converted into high-level semantic information. By taking into account both objective product qualities and subjective user ratings, this hybrid data representation improves the system's capacity to forecast consumer preferences. 【2:4-5】

Using both item-group and user-item interactions, the recommendation engine uses a cluster-based collaborative filtering technique. The method finds the top-N nearest neighbors in the expanded matrix and applies a weighted average deviation model to forecast ratings.. The prediction for user i on item k is computed using the following equation:

$$P_{i,k} = \underline{R_k} + \frac{\sum_{n \in N} \quad w_{n,i} \left(R_{n,k} - \underline{R_n} \right)}{\sum_{n \in N} \quad \left| w_{n,i} \right|}$$

where $P_{i,k}$ is the predicted rating, $\underline{R_k}$ is the average rating of item $k, \omega_{n,i}$ is the weight assigned to neighbor n, and N is the set of top-N neighbors. By combining collaborative filtering and visual features, this approach guarantees more accurate predictions, which improves MAE results and user satisfaction. 【2:6】

44,000 photos of fashion products with labels for gender and article category make up the dataset that Gharaei et al. used, which was obtained via Kaggle. To guarantee uniformity, preprocessing entails scaling every image to a standard 224x224 pixel size and normalizing pixel values to the [0,1] range. Additionally, to improve model resilience and avoid overfitting, augmentation techniques including rotation, flipping, and cropping are used. Using stratification, the dataset is divided into 80% for training and 20% for testing, guaranteeing equal representation in each category. 【4:4】

A 13-layer convolutional neural network (CNN) with convolutional, pooling, and fully connected layers serves as the foundation for the suggested model. While max-pooling layers minimize feature map dimensions while preserving important information, each convolutional layer uses a 4x4 kernel with ReLU activation to extract spatial features. For binary classification applications like gender detection, a final sigmoid layer is employed.

Training utilizes a categorical focal loss function defined by:

$$FL(Pt) = -\alpha_t (1 - Pt)^{\gamma} \log \log (Pt)$$

where γ modifies the emphasis on challenging cases and a_t serves as a balance element. For adaptive gradient descent, the Nadam optimizer is used to improve stability and convergence speed. This training regime streamlines the recommendation process by allowing the network to do feature extraction and classification at the same time.【4:5-6】

The recommendation system matches user-uploaded photos with database entries by using cosine similarity. Feature vectors extracted from the CNN are compared using the following formula:

$$\cos \cos (\theta) = \frac{A \cdot B}{\|A\| \|B\|}$$

where A and B represent the feature vectors of the product image and user input, respectively. The algorithm creates top-N recommendations that are both visually and contextually appropriate for the user by rating items according to similarity scores. This approach solves the cold-start issue for new products by guaranteeing quick, scalable, and highly accurate recommendations.【4:6-7】

In order to fully capture user preferences, Lei et al. suggest a model that incorporates both visual and non-visual contextual variables, such as brand, color, and texture. Items and users are represented as vectors, denoted as $I = \{I_1, I_{2,\dots,} I_n\}$ and $U = \{U_1, U_2, \cdots \cdots U_m\}$, respectively. Visual attributes are obtained using a CNN model that has already been trained, whereas non-visual features are taken from metadata.. This combination makes it possible for the system to forecast matching scores according to visual and contextual significance, which is crucial for suggestions that are based on aesthetics.【5:4-5】

To arrange items into clusters with comparable visual and contextual characteristics, the system uses hierarchical clustering. Cosine similarity is used to determine the degree of matching between a candidate item and previously purchased items; temporal relevance is taken into account by adjusting for decay:

$$M(i,j) = \delta \cdot sim(I_i, I_j) + (1 - \delta) sim(C_i, C_j)$$

Where M(i,j) is the matching score, δ controls the weighting between visual and non-visual features, and sim represents similarity functions. By lowering computational cost, this clustering-based method allows for effective large-scale matching without sacrificing precision.【5:5-6】

Using the following predictive model, the recommendation score is calculated by combining user preferences and matching strength:

$$\gamma^*_{u_i} = \sum_{C \in N(I_i)} M(C, I_i) \cdot \gamma_{u_i}$$

where $\gamma^*_{u_i}$ is the final recommendation score, $M(C, I_i)$ is the matching strength between cluster C and item I_i, and $N(I_i)$ denotes the neighborhood set of I_i. This hybrid model provides context-aware, tailored recommendations that greatly increase user satisfaction and purchase likelihood by striking a balance between preference and matching. 【5:6-7】

In order to capture a variety of datasets from user interactions, including purchase histories, social media activity, and product reviews, the article describes a multi-phase data collection approach. To extract valuable information like item attributes and user preferences, these datasets undergo preprocessing. To create strong user profiles, explicit feedback—such as product ratings—and implicit feedback—such as browsing habits—are combined. 【7:4】

Resizing, normalization, and feature extraction using deep learning models are examples of preprocessing for image-based data. Techniques like Term Frequency-Inverse Document Frequency (TF-IDF) are frequently used to tokenize and vectorize text data. 【7:5】

A variety of recommendation algorithms are trained using these preprocessed datasets. A number of algorithmic models that are suited to various input data types are examined. Convolutional Neural Networks (CNNs) are employed for feature extraction and image classification.. A typical CNN model comprises multiple convolutional layers followed by pooling layers, where the activation function f(x) is often ReLU (Rectified Linear Unit):

$$f(x) = (0, x)$$

To create item embeddings, the output is processed through completely connected layers.
Temporal dependencies in user interactions are captured by applying Recurrent Neural Networks (RNNs) to sequential data. The network can maintain long-term dependencies thanks to the Long Short-Term Memory (LSTM) variation, which solves the vanishing gradient issue:

$$h_t = tan\ tan\ h(w_h h_{t-1} + w_x x_t + b_h)$$

where ht represents the hidden state at time t, and w_h, w_x, and b_h are learnable parameters.
The study places a strong emphasis on using a variety of evaluation measures to gauge model effectiveness. 【7:11】

F1 Score, Precision, Recall, and Root Mean Square Error (RMSE) are examples of common metrics. RMSE is calculated as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{1=1}^{N} \quad (P_i - \gamma_i)^2}$$

where N is the number of predictions, P_i is the predicted rating, and γ_i is the actual rating 【7:7】

The authors extract features from fashion photos using a pre-trained ResNet50 model. To modify this model for the particular objective of fashion recommendation, transfer learning is used. During the training phase, the network is adjusted by swapping out the last layers to better fit the classification objective. Convolutional layers are used in the neural network's design to extract features, while fully linked layers are used for classification:

$$Output = Soft(w \times x + b)$$

where x is the feature vector, and W and b are the weight matrix and bias, respectively【9:3】

Conclusion:

To sum up, our hybrid recommender system delivers notable improvements in how customers purchase apparel and other goods from a variety of businesses. The system offers highly customized recommendations that adjust in real time to user preferences by fusing collaborative and content-based filtering methods with an easy-to-use swipe-based interface. This method presents products that closely match changing tastes and fashions, which not only makes shopping easier but also increases consumer pleasure.

Through the analysis of interaction patterns and preferences, the system provides vendors with profound insights into buyer behavior. Retailers can better anticipate trends, customize marketing campaigns, and optimize inventory thanks to this data-driven insight. Businesses may increase client retention and boost revenue by utilizing these insights to develop more tailored and interesting shopping experiences. In the end, this technology creates a more responsive and dynamic marketplace that helps both consumers and sellers by bridging the gap between retail offerings and consumer expectations.

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