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Abstract. In the clothing industry, design, development, and procurement teams have been affected more than any other industry and are constantly under pressure to present more products with fewer resources in a shorter time. The diversity of garment designs created as new products is not found in any other industry and is almost independent of the size of the business. Science4Fashion is a semi-autonomous intelligent personal assistant for fashion product designers. Our system consists of an interactive environment where a user utilizes different modules responsible for a) data collection from online sources, b) knowledge extraction, c) clustering, and d) trend/product recommendation. This paper is focusing on two core modules of the implemented system. The Clustering Module combines various clustering algorithms and offers a consensus that arranges data in clusters. At the same time, the Product Recommender and Feedback module receives the designer's input on different fashion products and recommends more relevant items based on their preferences. The experimental results highlight the usefulness and the efficiency of the proposed subsystems in aiding the creative fashion process.

Keywords: Fashion Data · Mixed Data · Consensus Clustering · Recommendation System · Collaborative Filtering

1 Introduction

The clothing industry is one of the most fast-growing sectors, with many employees around the world. Fashion brands need to adapt to the fast-fashion model to fulfill their customers' needs on time. Consequently, fashion industry designers deal with immense pressure for delivering an increasing number of products, with strict deadlines and limited resources. To this end, the creative department of a fashion designing company has several tasks that need to be completed before focusing on the newest collection. These are inspiration research (from previous exhibitions, social media, photo galleries, e-shops, and many more), trend analysis of the upcoming shows, and compliance to the company's product quality

standards. Thus, a designer must fulfill the creative process through a series of menial tasks.

This paper is an extension of our previous work [1], which introduced a digital assistant for fashion designers. Science4Fashion System is a combination of a clothing recommendation and a design assistant system that takes simple and easy-to-fill high-level configuration instructions and automates the aforementioned menial and time-consuming tasks. Some examples are (a) the collection of data from both internal (company databases and trend guides) and external sources (e-shops, social media, trend sites), (b) the data annotation, (c) clustering relevant fashion products to influential groups, and many more. This paper focuses on two of the core modules of the Science4Fashion system: the Clustering and the Product Recommender and Feedback Module.

For the remainder of this paper, Section 2 lists related work in the fields of clustering and recommendation systems, while Section 3 introduces the proposed methodology. Next, in Section 4 we present the datasets and results. Finally, in Section 5, we summarize our work, we offer the challenges and future work.

2 Related Work

Several research works have been presented in the domain of the clothing data analysis field, including clothing classification and clustering, feature extraction based on both images or text, and clothes recommendation.

Recent works in clustering techniques serve the fashion industry by providing insights to drive trend forecasting, new product designs, and improve recommendations. In [2] presents Rough Mean Shift Clustering, a soft clustering approach used to assist the process of product forecasting by discovering latent relationships between fashion attributes from unlabeled and ambiguous image data. Additionally, in our previous work [1], partition-based, hierarchical, and model-based algorithms were employed in the task of clustering products, according to their categorical and numerical attributes.

An extensive study on clothing recommendations systems has been made by Congying Guan et al. [3], including content-based and collaborative approaches. A hybrid system has been proposed by Xiaosong Hu et al. [4] exploiting both clothing information and user ratings while achieving better results using only the color attribute. Finally, an Advanced User-Based Collaborative Filtering algorithm has been developed by Yu Liu et al. [5], applied on the Tmall.com dataset with higher evaluation metrics than the traditional techniques.

Even though the State-of-the-Art presented above provides concrete solutions to their respective problem/field, none of them allows for a holistic approach to the real-life challenges faced by the fashion industry during the creative process. The current work proposes an AI-enabled system, facilitating the clothing products design, mainly targeting product concept development. The ultimate goal is to provide personalized suggestions to inspire designers towards fashionable products. More specifically, it is an end-to-end system that acts as a personal assistant. One great differentiator is the Product Recommender and User Feed-

back module. This module is implemented using a combination of (a) a hybrid algorithm for product ranking and recommendation, exploiting the benefits of different baseline algorithms, and (b) a hierarchical clustering method to improve algorithm results.

3 Methodology

This section presents an overview of the proposed methodology for clustering the fashion products included in the dataset and recommending potentially insightful products to the end-user. The Clustering module creates meaningful clusters of similar products. At the same time, it facilitates and refines the recommendation system input to provide the results in near real-time and enhance the User Experience. Furthermore, the Product Recommender is responsible for delivering personalized and relevant results by employing a feedback mechanism.

3.1 Clustering Module

Most clothing datasets used for the clustering experiments consist of numerical and categorical data that describe fashion apparel attributes such as fabric composition, genre, season, manufacturer, retail price, and more.

After data preprocessing, the features are used by a set of unsupervised clustering algorithms to create meaningful groups used as input into the Recommender module. Specifically, a) K-Means [6], b) Fuzzy C-Means (FCM) [7] and c) BIRCH [8] are employed. The generated clusters from all algorithms are encoded in a similarity matrix, used as input for an Agglomerative Hierarchical clustering model used for the consensus clustering.

The following paragraphs introduce the clustering module, starting with the data preprocessing stage and the feature extraction methodology, followed by the proposed consensus mechanism. Lastly, the metrics used for the clustering evaluation are presented.

Mixed Data Preprocessing The first step of preprocessing is comprised of a data cleaning process that involved normalizing the numerical attributes and filling out missing values. The next step is the feature selection process.

Due to the nature of the dataset, the Factor Analysis for Mixed Data (FAMD) method [9] was used to create features out of the quantitative and qualitative attributes of the dataset. In general, Factor Analysis is a statistical method applied in data exploration and dimensionality reduction. In essence, FAMD can be described as the combination of two other Factor Analysis methodologies, the Principal Component Analysis (PCA) [10] and the Multiple Correspondence Analysis [11]. An essential feature of FAMD is that it balances the contribution of both the categorical and the numerical attributes [9], by converting to one-hot columns and then scaling the former and normalizing the latter. Similarly to PCA, the final FAMD embedding is a reduced sub-space that maps the correlation between categorical and numerical data.

In this case, the final 12 product attributes that represent the fashion dataset were transformed to 3-dimensional embeddings. Based on the explained inertia of each component, the first 2 FAMD components were selected as features by the least number of FAMD components. These embeddings are used as input to the clustering algorithms.

Consensus Clustering was a methodology initially motivated by the need to assess the "stability" of the produced clusters. A common symptom of clustering algorithms is that variations in the initialization strategy and parameterization of the algorithm can affect the resulting groups. To this end, consensus clustering was conceptualized by Monti in [12] as a method to reconcile perturbed datasets resulting from re-sampling of the data.

In this work, consensus clustering is used as an ensemble clustering algorithm [13] that combines different clustering models to unveil latent relationships between data. In other words, consensus clustering is used to formalize the agreement between different clustering algorithms.

The consensus of the different clustering results is achieved through a consensus matrix that describes the co-occurrence of data points in the same cluster. The consensus matrix is obtained as the normalized sum of the connectivity matrices produced by the different clustering outcomes. Initially, according to Monti, the consensus matrix C is a NxN matrix defined as follows:

$$C(i,j) = \left(\frac{\sum_{h=1}^{H} M^{(h)}(i,j)}{\sum_{h=1}^{H} I^{h}(i,j)} \right) \tag{1}$$

where M^h a list of NxN connectivity matrices resulting from the perturbed datasets obtained by re-sampling, and I^h is the indicator matrix. The value of (i,j)-th entry is equal to 1 if both i and j belong to the same cluster, or 0 otherwise. An essential property of the consensus matrix is that it acts as a similarity measure of the different data points.

In the proposed clustering module, to produce a more defined clustering result, a Radial Basis Function (RBF) kernel [14] is applied on the consensus matrix. The RBF kernel is used to exaggerate the distances captured by the consensus matrix by decreasing the Euclidean distance and is given by:

$$k(x_i, x_j) = exp(-\frac{d(x_i, x_j)^2}{2l^2}) \tag{2}$$

where d is the Euclidean distance and $l > 0$ is a kernel's scalar parameter. The resulting enhanced consensus matrix is used as an input to an Agglomerative hierarchical clustering model to produce the final clustering reconciliation using complete linkage.

3.2 Product Recommender and Feedback Module

Recommendation systems are encapsulated in the background of almost most personalization systems and aim to propose to the user options catered by the

system (movies, books, services, clothes). In general recommendation strategies, can be categorized into three main types: a) content-based (CB) methods [15], which extract feature vectors describing the items and suggesting similar items according to user's preferences, b) collaborative filtering (CF) based methods [16], which make suggestions based on user preference similarities since users that have rated the same items are more likely to have similar dispositions, and c) Hybrid methods [17], which combine the two recommendation mentioned above methods, to eliminate each method's restrictions and benefit from their complementary advantages.

Collaborative Filtering - Singular Value Decomposition (SVD) Singular Value Decomposition is a table factorization technique, where a table $A(m \times n)$ is represented as follows:

$$A = U \times \Sigma \times (V)^T \tag{3}$$

where: U is a square matrix with dimensions $m \times r$, V^T is the inverse matrix of V with dimensions $n \times r$ and Σ is a diagonal matrix $r \times r$.

Matrix Σ contains the eigenvalues in descending order. The users and the clothing products can be represented in $r \times r$ dimensional space by utilizing the U and V matrices.

The Recommendation system begins by splitting the available samples into the training and testing dataset. The Singular Value Decomposition is applied to the training dataset, and the resulting recommendations are evaluated using the testing dataset. When the optimal parameter k is selected, the system creates the output data with the optimally recommended items.

Collaborative Filtering - Neural Collaborative Filtering (NCF) As mentioned earlier, the implementation with SVD recommends products based on the users' inner product and product tables. However, the inner product can only detect the latent vectors' linear combinations. To identify more complex affinities, we apply neural networks in collaborative filtering.

The architecture of NCF includes [18]:

- *Input Layer*: transforms a sparse vector for a user and item identification to binary.
- *Embedding Layer*: is a fully connected layer that projects the sparse representation to a dense vector.
- *Neural Collaborative Layers*: use multi-layered neural networks to determine the latent vectors and predict the scores.
- *Output Layer*: provides the output of the neural network.

NCF is described by the following formula:

$$\hat{y}_{ui} = f(\mathbf{P}^T \mathbf{v}_u^U, \mathbf{Q}^T \mathbf{v}_i^I | \mathbf{P}, \mathbf{Q}, \Theta_f) \tag{4}$$

where: P is the latent factor matrix for users,$\mathbf{v}$ is the binarised vector for a user and item identification, Q is the latent factor matrix for items and Θ_f are the model parameters.

Table 1: Structure of the multi-layers Neural Network (Collaborative Filtering)

Layers	**Neurons**	**Activation Function**	**Dropout Rate**	**Weights Initialization**
Layer 1	4096	ReLu	50%	he_normal
Layer 2	2048	ReLu	50%	he_normal
Layer 3	1024	ReLu	30%	he_normal
Layer 4	512	ReLu	30%	he_normal
Layer 5	256	ReLu	30%	he_normal
Layer 6	128	ReLu	30%	he_normal
Layer 7	1	Sigmoid	0%	Glorot normal

The layers of the neural network created for this approach are presented in table 1, with each layer's size decreased in half.

The input layer of the training dataset is transformed to a sparse matrix with the use of one hot encoding [19]. The selected activation function is the ReLu in all layers, except the last one, where the sigmoid function is used. The reason for not using sigmoid function values, which vary from 0 to 1, is that they may result in saturation, which means that the neurons don't work correctly when the value of the function is close to 0 or 1. On the other hand, ReLU function [20] is the answer to the saturation problem, and it is the proper function for a system with sparse data.

The input training dataset is entered in the embedding layer, where the dense vector is created. The embedding layer dimensions are the $totalUsers \times factors$ and accordingly $totalItems \times factors$, where the number of factors is 70.

Next, the vector is provided as input to the multi-layer neural network. The neural network design begins with a broad layer (many neurons), and half in the number of neurons decreases every consequent layer. A small number of hidden layers enable capturing the abstract nature of the data [21]. In general, several layers and parameters were used to develop the neural network. The proposed method with the seven layers and the specific parameters was the best result of all the experiments conducted.

Content Based - Random Forest Random Forests [22] are ideal models for analyzing dataset features, as they combine classification methods that use decision trees as classifiers. For creating a decision tree, the input data are imported in the tree's root node, and every other node contains a subset of their father node data. The father node data split into two or more subsets is based on the Gini index, entropy, or misclassification error. Every tree of the random forest can be expanded to its maximum depth or a limit depth selected before the training process.

In the proposed implementation, the Random Forest is initiated by injecting the user ratings for every cloth into every random forest. In this context, the Optuna library is used for finding the optimal values for the number of estimators and the maximum depth, which are the most critical parameters for the produced random forest models.

Content Based - Neural Networks In this variation of the Content-Based Recommendation approach, every user rates several clothing products, and these ratings are given as input to the multi-layer neural network. The neural networks' architecture has many similarities with the neural network described in the 3.2. The parameters of the network are specified in Table 2.

Table 2: Structure of the multi-layers Neural Network (Content Based)

Layers	**Neurons**	**Activation Function**	**Dropout Rate**	**Weights Initialization**
Layer 1	2048	ReLu	20%	he_normal
Layer 2	1024	ReLu	20%	he_normal
Layer 3	512	ReLu	10%	he_normal
Layer 4	256	ReLu	10%	he_normal
Layer 5	1	Sigmoid	0%	Glorot normal

Hybrid The hybrid models combine two or more methods to benefit from all their advantages and eliminate their restrictions. The proposed hybrid system employs the methods mentioned above and creates a system of two recommendation packages. The first package suggests using the Regression Voting Ensemble in which the predictions are the average of contributing models. On the other hand, the second package endorses a linear regression model. The training set, given as input and used for the methods' training, is 70% of the initial dataset, and the testing set the remaining 30%.

4 Experimental Results

Having discussed the methodology behind the proposed system, we present the results of the clustering and recommendation modules separately in this section.

4.1 Fashion Data Clustering

The data collection module of the fashion trend recommendation system, provides the data to the clustering and the recommendation modules. These data consist of 22 product attributes described by both quantitative and qualitative variables.

A preprocessing pipeline was established to clean up the noisy content collected by the social media platforms. The 12 remaining attributes and 1224 records are transformed using the FAMD method. According to the variability of each component, the first two out of the total 3 FAMD components are used as the clustering features.

For the clustering experiments, the employed algorithms mentioned earlier are used as baseline models and are compared against the proposed Consensus clustering model. Several iterations of each algorithm are executed to select the

Data Types	Product Attributes
Numerical	Production Price, Retail Price, Sample Price, Wholesale Price
Categorical	Business Unit, Collar Design, Colors, Description, Fit, Foreign Composition, Gender, Inspiration Background, Length, LifeStage, Neck Design, Product Category, Product Subcategory, Production Manufacturer, Sample Manufacturer, Sizeset, Sleeve, Trend Theme

Table 3: Product attributes of the clothing apparels dataset

Table 4: Comparison of baseline clustering algorithms and Consensus Clustering.

Metric	K-Means	Birch	Fuzzy C-Means	Consensus Clustering
Silhouette	0.53	0.47	0.53	**0.93**
Davies-Bouldin	0.71	0.70	0.71	**0.18**
Calinski-Harabasz	1419.31	1096.08	1419.22	**18274.25**

proper parameters. Regarding the FCM model, the fuzzifier parameter was set to 2. The ideal number of clusters was chosen using the Scaled Partition Entropy criterion, and a "hard" clustering result was produced by applying the maximum likelihood principle. The optimal number of clusters for the rest of the models was decided using (a) the Silhouette score [23], (b) Davies-Bouldin Index score [24], and (c) the Calinski-Harabasz Index score [25].

Table 4 demonstrates the superiority of the proposed clustering method, as it outperforms the rest in all of the examined metrics. Specifically, the higher Silhouette and Calinski-Harabasz scores are an indication of high density and separation. At the same time, a lower Davies-Bouldin index relates to a model with better separation between the clusters.

Furthermore, the obtained clustering results are illustrated in Figure 2, where the Consensus clustering, K-Means, and maximum likelihood FCM identified three clusters, whereas BIRCH revealed six groups. Also, Figure 1 illustrates how the Consensus clusters capture the "Gender" and "Product Category" attributes of the fashion apparel dataset.

4.2 Product Recommender and Feedback Module Experiments

Dataset Two diverse datasets were used to train and evaluate the Product Recommender and Feedback module (Table 5). The datasets were used to prepare the initial recommendation model and consist of 1700 clothing products from the ASOS website rated from 100 users. The main difference between the two datasets lies in the percentage of rated clothes per user, 30 percent for the first one and 60 percent for the second, while the clothes rating can vary from zero to ten [0,10]. The annotation for the rating of the clothing datasets was performed programmatically in a pseudo-random way.

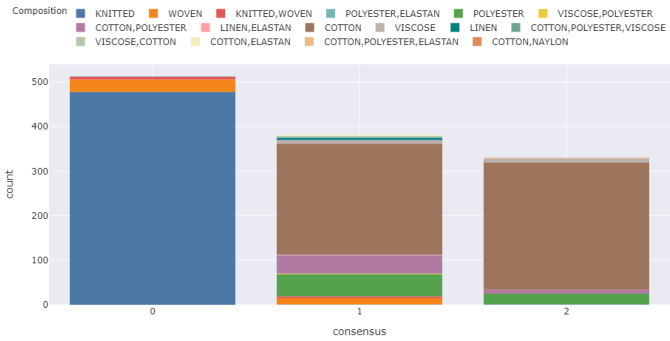
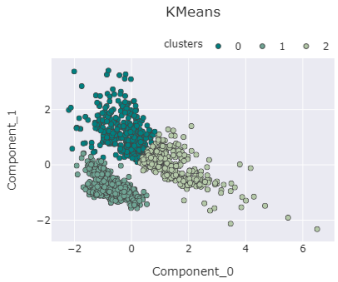
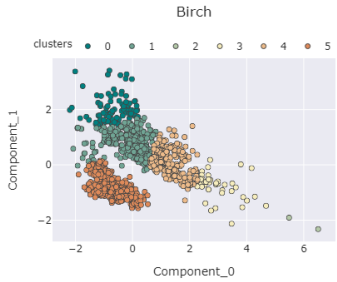


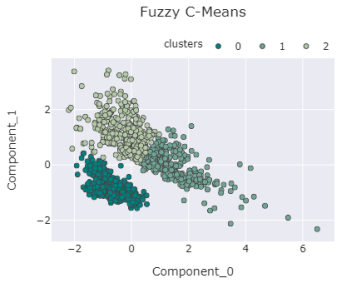
Fig. 1: Visualization of how the Consensus clusters capture the "Fabric Composition" attribute, where the first cluster consists mainly of knitted and woven products, whereas the second and third clusters contain apparels made out of polyester and cotton



(a) K-Means: 3 clusters



(b) Birch: 6 clusters



(c) FCM: 3 clusters

(d) Consensus clustering: 3 clusters

Fig. 2: Visual comparison of the different clustering models

Table 5: Dataset elements.

Dataset Name	Products	Users	Ratings Number	Ratings Percentage	Ratings Interval	Number of Categories
Asos30	1700	100	50k	30%	[0,10]	10
Asos60	1700	100	100k	60%	[0,10]	10

Results In Table 6 we demonstrate the results of the techniques discussed in chapter 3 for the two training datasets. Also, Table 7 contains the evaluation metrics for the evaluation of our implementation.

Table 6: Techniques Results for Asos Datasets

(a) **Asos30 Dataset**

Model	Accuracy	Recall	Precision	F1 Score
SVD	0.78	1.00	0.78	0.87
CF-NN	0.78	1.00	0.78	0.87
CB-RF	0.77	0.96	0.78	0.86
CB-NN	0.76	0.89	0.81	0.84
Hybrid	0.81	0.98	0.82	0.89

(b) **Asos60 Dataset**

Model	Accuracy	Recall	Precision	F1 Score
SVD	0.82	1.00	0.82	0.90
CF-NN	0.83	1.00	0.83	0.91
CB-RF	0.80	0.97	0.79	0.87
CB-NN	0.81	0.91	0.84	0.87
Hybrid	0.84	0.97	0.84	0.90

Table 7: Evaluation Metrics

(a) **Asos30 Dataset**

Model	RMSE	MAE
SVD	2.73	2.34
CF-NN	2.75	2.41
CB-RF	2.35	1.85
CB-NN	2.49	1.87
Hybrid	2.37	2.02

(b) **Asos60 Dataset**

Model	RMSE	MAE
SVD	2.55	2.17
CF-NN	2.47	2.04
CB-RF	2.14	1.65
CB-NN	2.10	1.58
Hybrid	2.10	1.74

In the Asos30 dataset, the first three techniques have similar results; the accuracy varies from 77% to 78%, recall from 96% to 100%, and f1 score from 86% to 87%. The lower recall value is attributed to the CB-NN technique and the best overall performance to the hybrid method. More specifically, the hybrid method presents the best results for all the metrics, except for the recall value, which is close to the best value (98%).

As far as the evaluation metrics are concerned, the SVD and CF-NN techniques have similarly low error values, with the RMSE varying from 2.73 to 2.75 and the MAE from 2.34 to 2.75. The CB-RF and CB-NN approaches also have similar error values. The best performance with the best evaluation metrics, 2.29 for the RMSE and 1.83 for the MAE, belongs to the hybrid method.

The results for the Asos60 dataset are similar to the Asos30, both for the accuracy, recall, precision, and evaluation metrics.

Based on the illustrated results, the hybrid method seems to be the optimal approach for the Recommendation system on the provided clothing garment dataset. It outperforms the individual techniques in most metrics utilized.

In figure 3, a visual representation of the hybrid method results for the query *"Coats for women"* is provided. In the first row of the figure, there are women coats already rated by the user. In contrast, there are unrated clothes with the Recommendation system in the second row to predict their rating based on the user preferences. The coats presented by the Recommendation system as the best fits for the user are quite similar to the clothes in the first row, highlighting the accuracy and the usefulness of the proposed approach.

Fig. 3: Recommended clothes for the query: "Coats for women"

5 Conclusion and Future Work

Nowadays, the clothing industry has become one of the most profitable markets and moves towards fast fashion. Thus, artificial intelligence techniques have been adopted by most fashion houses. To this end, this paper has presented the clustering and the recommendation core modules of Science4Fashion, a modular digital assistant for fashion designers.

Specifically, the paper demonstrated an aggregated clustering approach, where the clustering insights produced from different algorithms are combined to a consensus clustering solution. The method was applied in a mixed dataset of categorical and numerical attributes obtained from retail websites and social

media platforms. The consensus clustering approach produced more dense and segregated clusters than applying the methods individually.

Furthermore, different recommendation techniques were used as a base for the digital assistant's Product Recommender module. A hybrid approach of collaborative filtering and content-based methods outperformed the recommendations produced by applying each technique individually.

The clustering module's future extensions involve experimenting with FAMD features and various innovative clustering methods, such as spectral clustering and methods involving neural networks. Moreover, different feature encoding approaches can be explored where numerical attributes are transformed into categorical quantization techniques. In this case, K-Modes [1] algorithm, a variation of K-Means could be applied to cluster categorical data.

Extensions can also be applied to the Product Recommendation module, such as introducing pre-trained models from real-world datasets containing ratings from end-users and designers to optimize the recommendations' precision. Using user favorites, dashboards, and product sales as input would improve the Recommendation system results. Finally, the system can also include a negative vote for the clothes characterized as irrelevant by the user.

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