PRODUCT RECOMMENDATION SYSTEM(FASHION)

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***Abstract*—** *When a new customer visits an e-commerce website for the first time and has no previous purchase history, the most popular products offered on the site are recommended. After he or she makes a purchase, the recommendation system refreshes and recommends other products based on their previous purchases and ratings from other users on the website. Collaborative filtering approaches are used.*

***Keywords*—** **Machine Learning, Deep Learning**

I. INTRODUCTION

Clothing is a type of sign that reflects a person's feelings through their outside look. It contains details about their preferences, faith, personality, profession, social standing, and outlook on life. As a result, clothing is thought to be a nonverbal means of communication as well as a significant aspect of people's exterior look. Consumers can now track current fashion trends around the world, which influences their decisions, thanks to recent technological breakthroughs. Consumer fashion choices are influenced by a variety of elements, including demographics, geography, personal tastes, interpersonal influences, age, gender, season, and culture. An effective recommendation system is a critical component of running a successful e-commerce firm. Fashion recommendation systems (FRSs) are programs that make recommendations to customers based on their browsing and purchasing history.

II. RECOMMENDATION SYSTEM

A recommendation system is a method for users to make decisions in a multidimensional information environment. RS is also an e-commerce platform that assists customers in finding products based on information about their choices and interests. When there is a lack of personal information or understanding of the alternatives, RS can help augment social processes by utilizing the recommendations of other users. By providing tailored service, exclusive material, and personalized recommendations, RS alleviates the problem of information overload that consumers frequently face. The foundation of any state-of-the-art recommendation system is built throughout several phases of the recommendation system. The information-gathering phase, the learning phase, and the recommendation phase are all defined as such.

II.1. Information Collection Phase

In this phase, relevant information about a user is gathered to create a user profile or model based on the user's attributes, behaviors, and the content of the sites they have visited that can be used in prediction phase tasks. The right creation of a user profile or model is required for a recommendation agent to perform correctly. When the system has all the necessary information about the user, it may provide a quick yet relevant recommendation. As a result, the capacity of a suggestion or recommender system to identify users' present preferences or choices is critical to its performance.

The recommendation system is built on three different types of input: explicit feedback, implicit feedback, and hybrid feedback. Explicit feedback, which includes users' explicit input about their interest in or choice of a product, must be of high quality. User ratings determine the accuracy of the prediction or recommendation. In addition to understanding users' preferences, which are gathered indirectly through observation of user behavior, implicit feedback is critical. Even though this method does not necessitate as much work from the consumers, it is frequently seen as less accurate [57,66]. The term "hybrid feedback" refers to a mix of explicit and implicit feedback. It can be done by using implicit feedback data as a check on explicit feedback ratings, or by giving users the option to submit feedback only if they clearly declare their desire in doing so.

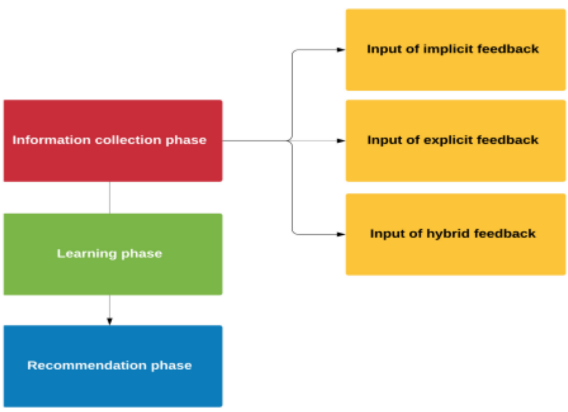


FIGURE1. PHASES OF RECOMMENDATION PROCESS

II.2. Learning Phase

Based on the feedback gathered during the information gathering phase, a learning algorithm is used in this phase to filter and exploit the users' features. The learning algorithms employed in this phase aid in the identification of relevant patterns for usage throughout the recommendation step.

II.3. Recommendation Phase

The item types that a user or consumer may like are recommended during the recommendation phase. Recommendations can be made directly from the dataset collected during the data collection phase or from the system's observation of users' browsing history. Combining the learned information with the rating matrix can also be used to make recommendations for learning resources. In comparison to product content-based or another user preference-based collaborative model, researchers found that hybrid models enhanced recommendation accuracy.

III. Algorithms Models Used in Fashion Recommendation Systems.

The models most used in developing fashion recommendation systems are Resnet152 which is related to CNN (convolutional neural networks), k-nearest neighbor (kNN), Torch, Torch vision and cv2.

III.1. Convolutional Neural Networks (CNN):

A convolutional neural network (CNN) is made up of several convolutional layers, the number of which is determined by the desired recommendation system conclusion. Convolutional layers, filter size, and completely connected layers are all examples of these layers. To produce better results with maximum accuracy, researchers increase or reduce the network's depth. Kernel and batch sizes are set based on the layer's desired input/output. The ResNet architecture (with its three realizations ResNet-50, ResNet-101, and ResNet-152) was released in 2015 by Microsoft Research Asia and achieved excellent performance in the ImageNet and MS-COCO competitions. Residual connections, the central concept in these models, are found to considerably increase gradient flow, allowing for the training of much deeper models with tens or even hundreds of layers. Through their unique WordNet IDs, ImageNet classes are mapped to Wolfram Language Entities.

III.2. Recurrent Neural Network (RNN):

A recurrent neural network (RNN) is a feed-forward neural network with an internal memory that is a generalization of the feed-forward neural network. To handle sequences of inputs, RNN can use its internal state (memory). Depending on the research, there can be one too many input vectors and output nodes, which are not co-dependent. The input vectors' dimensions might be any size. From the number of input vectors to the number of states for the next cell, the hidden states change. ReLU is the most frequent activation function in RNN. Long Short-Term Memory (LSTM) networks are a modified version of RNNs that can more effectively remember past data in memory. Because LSTM solves the vanishing gradient problem of RNN, it is widely used to categorize, process, and predict time series data. For a fashion retailer, Wu et al. created a session-based recommendation model.

III.3. k-Nearest Neighbor (kNN):

The k-nearest neighbor (kNN) technique is a straightforward supervised learning approach that may be applied to classification and regression issues. When given fresh unlabeled data, it relies on labeled input data to produce output. It's a non-parametric algorithm, which means it doesn't make any assumptions about the underlying data distribution and doesn't generalize from the training data points. The algorithm's result is based on feature similarity.

III.4. Torch Vision and CV2:

Torchvision is a Computer Vision library that goes hand in hand with PyTorch. It includes tools for doing efficient image and video transformations, as well as pre-trained models and datasets. OpenCV (Open-Source Computer Vision Library) is a free and open-source software library for computer vision and machine learning. OpenCV was built to provide a common infrastructure for computer vision applications and to accelerate the use of machine perception in commercial products. Being a BSD-licensed product, OpenCV makes it easy for businesses to utilize and modify the code.

IV. CODE IMPLEMENTATION.

Dataset:

The Fashion product images dataset is taken from the Kaggle which consists of 44K products with 142 categories The below graph depicts the different categories.

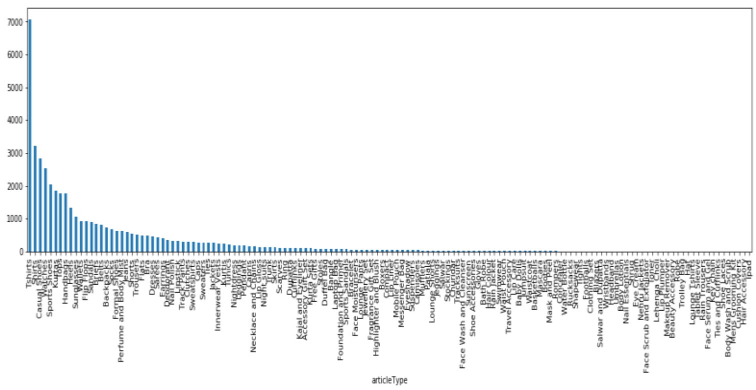


FIGURE2. GRAPH DEPICTING THE 142 CATEGORIES OF THE DATASET.

STEPS:

FEATURE EXTRACTION:

In the Feature Extraction Step, we used the Pytorch library, and another important library as mentioned above. First and foremost we have used restnet152 according to Wikipedia the Resnet is defined as **residual neural network** (**ResNet**) is an artificial neural network (ANN) of a kind that builds on constructs known from pyramidal cells in the cerebral cortex. Residual neural networks do this by utilizing *skip connections*, or *shortcuts* to jump over some layers. Typical *ResNet* models are implemented with double- or triple-layer skips that contain nonlinearities (ReLU) and batch normalization in between. The Resnet is used to avoid the problem of vanishing gradients, or to mitigate the Degradation (accuracy saturation) problem.

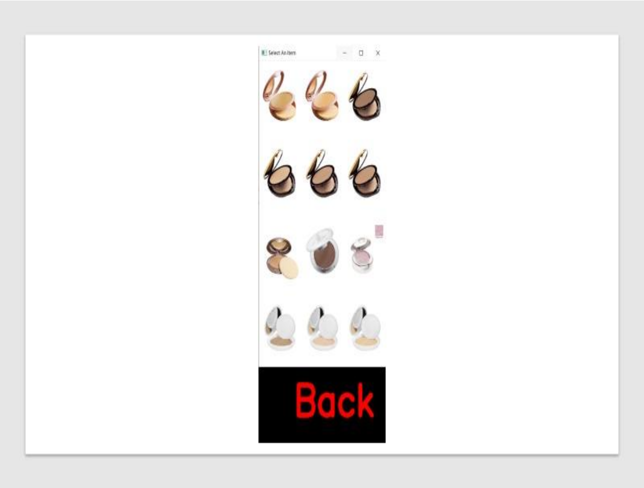
- The Pre-trained ResNet Model is Loaded
- The fully connected layer is stripped off.
- The model is set to evaluation mode
- Perform Image Transformation
- The 2048 image dimension is scaled to 224*224
- Perform Normalization using to tensor.
- The image is loaded using pillow library and the number of channels are checked using the get band function.
- The Pytorch variable is created for the transformed image.
- By extracting the important features, the output is loaded into the Features150.npy file.

DRAW:

- The necessary libraries are loaded.
- The Open CV is used to build an application.
- The set of 12 images are loaded to display on the screen they are chosen randomly.
- The images are concatenated horizontally and vertically for display
- A Function Mouse Click is created which returns the X, Y axis positions on the window
- The Image is selected based on the axis and image size.
- In Machine Learning the K- Nearest Neighbours Method the Euclidean distances are calculated.
- The features extracted before are taken and the distance is calculated to the 12 nearest neighbors and the images are displayed on the screen.

V. INPUT AND OUTPUT.

The Input is the images that are taken from the kaggle Fashion dataset which consists of the 44K images the features are extracted using the Res-Net 152 which is pretrained based on the image net visual database. The input is taken as the images which are 12 random categories of the data set and when the customer clicks on his desired category he is recommended with the items based on his choice.



VI. CONCLUSION.

Fashion recommendation systems have the potential to open new business options for merchants by allowing them to deliver personalized recommendations to customers based on data obtained from the Internet. They assist customers with locating items and services that closely fit their preferences. Furthermore, many state-of-the-art algorithms have been developed to recommend products based on interactions between users and their social circles. As a result, new research into incorporating social media photos within fashion recommendation algorithms has exploded in popularity. Based on academic literature on the issue, this research gave an overview of fashion recommendation systems, algorithmic models, and filtering strategies. The Fashion Recommendation System is built on the Res-Net 152 which is the pre-trained Deep convolution neural network on the Image Net Database. The K-NN Algorithm is used to find the k- nearest neighbors for the item selected by the customer. The Res-net 152 is used instead of traditional Recurrent Neural Networks and the Convolution Neural Networks. The Model has Loaded a large amount of dataset and fit it well and got the accurate output as seen above in the output image. Hence, the customer is recommended based on his previous purchase history.

VII. REFERENCES.

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