Fashion Recommender System

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CHAPTERS

Introduction

Project Overview

Problem Statement

Fashion enthusiasts often seek inspiration from websites like Pinterest to discover unique and trendy styles, with a desire to find similar clothing items for purchase.

Objective

Robust recommender system that suggests closely matched clothing items based on user inputs, simplifying fashion exploration and discovery.

Expected Outcome

1. Personalization: The recommendations is personalized to each user's preferences, taking into account their individual style, size, and other relevant factors.
2. Enhanced User Experience: Simplifies the process of finding and discovering fashion inspirations, making it easier for users to explore and purchase similar items.
3. Increased Engagement: Drives user interaction and exploration of fashion options, fostering higher engagement with the platform.
4. Improved Conversion Rates: Relevant and appealing recommendations enhance user preferences, leading to higher conversion rates and increased purchases.
5. Continuous Improvement: Adaptable system that learns from user feedback and incorporates new trends for accurate and up-to-date recommendations.

Data

Data

Our original dataset consists of approximately 590MB of data that consists of ~44,000 images of clothes.

The images have been scaled down as the original dataset is 25GB because of the following advantages:

1. Computational Efficiency: Enhance computational efficiency by reducing training time, memory usage, and computational resources required.

2. Faster Processing: Enable faster processing, leading to quicker recommendations and an enhanced user experience.

3. Reduced Noise and Variability: Helps filter out noise and focus on relevant patterns, improving the accuracy of recommendations.

4. Generalization: A scaled-down dataset improves generalization, aligning recommendations with broader fashion trends and preferences.

Model

ResNet50: Deep Learning Architecture

- **ResNet50** is a deep learning model introduced by Microsoft Research with 50 convolutional layers and skip connections, known for its outstanding performance in computer vision tasks.

- **Key Features:**
  - ➔ Deep structure with 50 convolutional layers
  - ➔ Utilizes skip connections to address vanishing gradients
  - ➔ Introduces residual blocks for learning complex representations

- **Applications:**
  - ➔ Image classification
  - ➔ Object detection
  - ➔ Image segmentation

- **Advantages:** Enables training of deeper networks with improved accuracy

- Widely used and achieved state-of-the-art performance on benchmark datasets like **ImageNet**

Model Used

Model Code Snippet

```
model = ResNet50(weights='imagenet',include_top=False,input_shape=(224,224,3))
model.trainable = False

model = tensorflow.keras.Sequential([
    model,
    GlobalMaxPooling2D()
])
```

Explanation

- Model: ResNet50
- Pre-trained on ImageNet dataset
- ‘include_top=False’ to exclude the final fully connected layer
- Input shape: 224x224 pixels with 3 channels (RGB)
- `model.trainable = False` to freeze pre-trained weights
- Sequential model with ResNet50 as the first layer
- GlobalMaxPooling2D layer for spatial dimension reduction and feature extraction

Test Results

User Given Image

Recommendation 1

Recommendation 2

Recommendation 3

Recommendation 4

Recommendation 5

- **Note**: The images lack clarity as they were scaled now
- The first three recommendations are much more closer to the user given image than the last two. This is because there are no other much more closer options available.

Future Work

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- **Scope of Evaluation:** As this is only a dataset of images, there is no scope of evaluation. Manual Evaluation or applying A/B testing by taking review from the customer could be beneficial.

- **Gender Classification:** The model does not categorise male and female clothing. Hence, it could give male clothing options for a girl and vice versa. This could be improved.

- **Incorporating External Factors:** Expand the predictive model by incorporating external factors that may influence the recommendation.

- **User Behavior Analysis:** Analyze user behavior and preferences to inform marketing, infrastructure, and service improvements recommendation.

References

- **Code:** https://github.com/Snigda0402/Fashion-Recommender-System
- **Dataset:** https://www.kaggle.com/datasets/paramaggarwal/fashion-product-images-small

THANK YOU!