FASHION CLOTHING MACHINE LEARNING

PROJECT

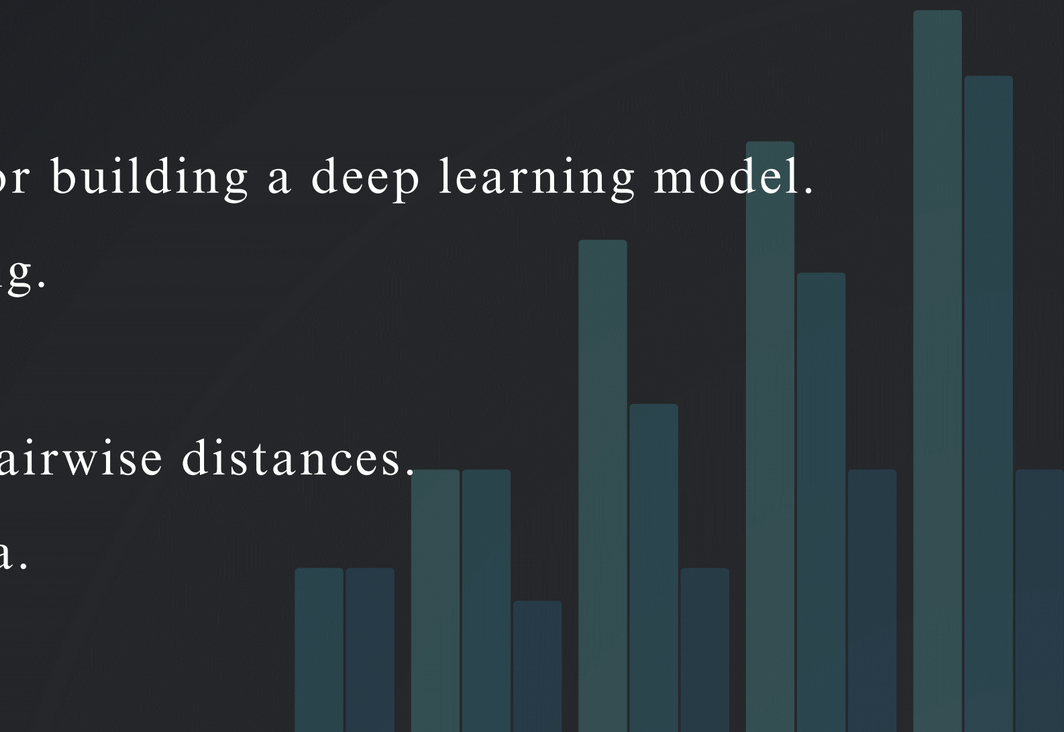
Ata Güneş & Mertcan Duran

CONTENTS

1.1 Importing The Necessary Libraries & Loading The Data

1. Libraries Used:

1. **Data Manipulation and Visualization**
   - NumPy and Pandas: For efficient data manipulation.
   - Matplotlib and Seaborn: Visualization of data and results.
2. **Deep Learning with Keras**
   - ImageDataGenerator: Augmentation of image data.
   - Sequential, Dropout, Flatten, Dense: Components for building a deep learning model.
   - Applications: Pre-trained models for transfer learning.
3. **Pairwise Distances and HTTP Requests**
   - Sklearn.metrics.pairwise_distances: Calculation of pairwise distances.
   - Requests: Making HTTP requests for additional data.



4. Image Processing

- **PIL (Python Imaging Library): Handling image processing tasks.**

5. Serialization and Deserialization

- Pickle: Serialization and deserialization of Python objects.

6. Date and Time Handling

- Datetime: Working with dates and times.

7. Streamlit (Commented Out)

- Streamlit: Library for creating web applications (commented out in this script).

8. Interactive Visualizations with Plotly

- Plotly Figure Factory, Graph Objects, Express: Creating interactive visualizations.

9. Displaying Images

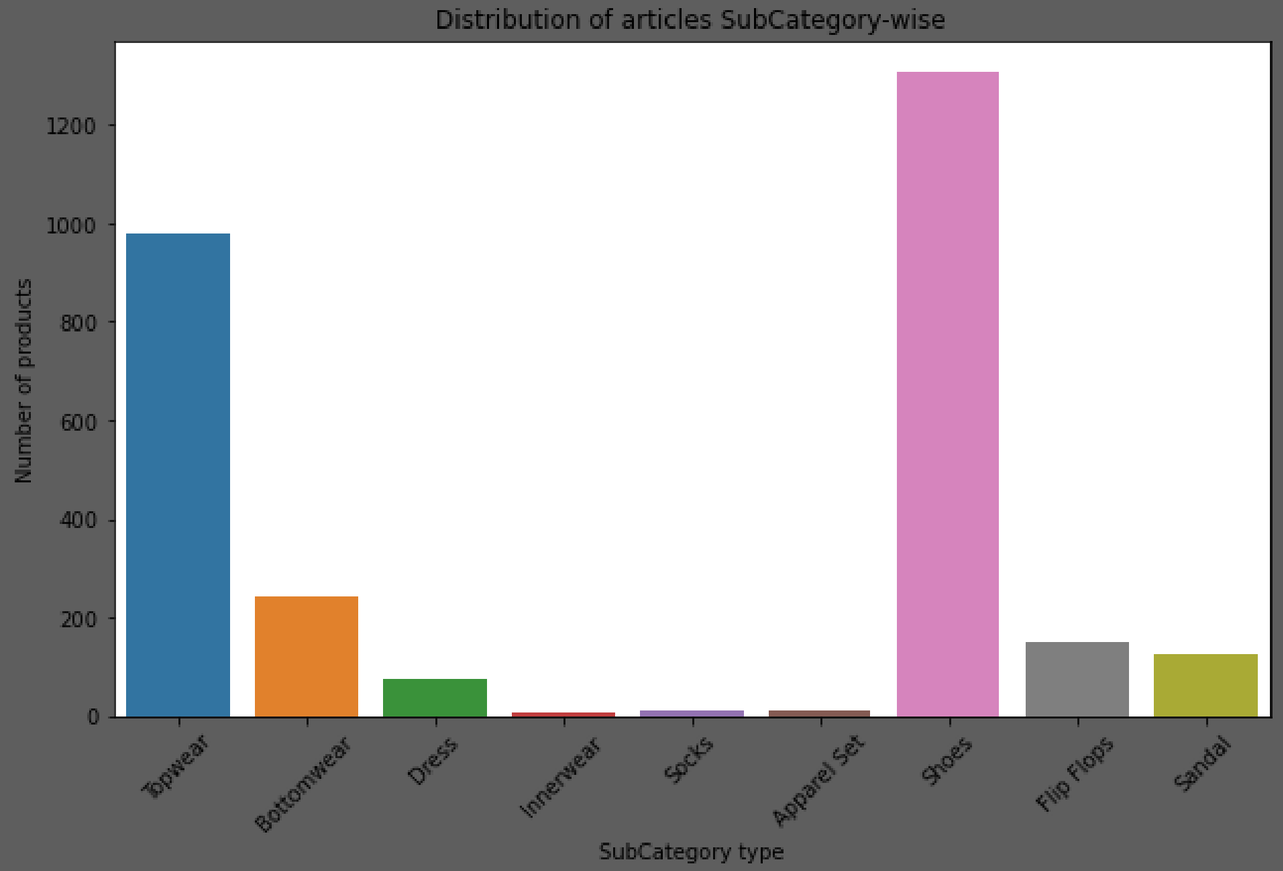
- IPython.display: Displaying images in Jupyter notebooks.

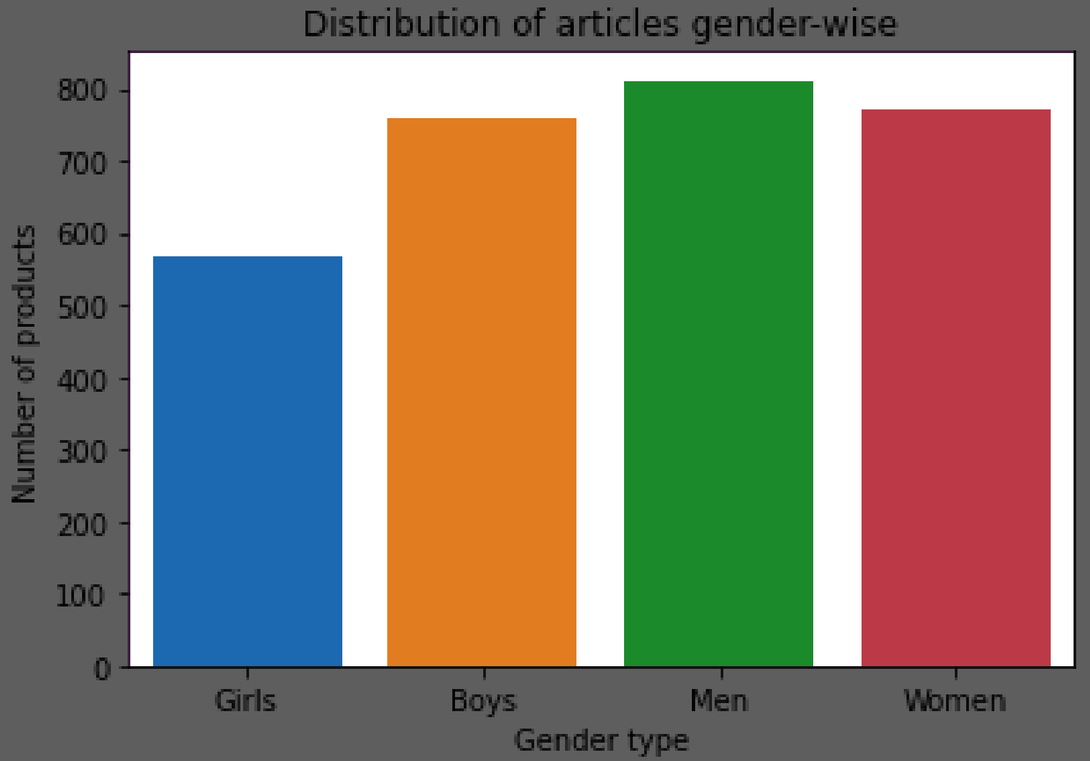
1.2 Basic statistics - Number of products, subcategories & gender

- **Total number of products : 2906**
- **Total number of unique subcategories : 9**
- **Total number of unique gender types : 4**

	ProductId	Gender	Category	SubCategory	ProductType	Colour	Usage	ProductTitle	Image	ImageURL
0	42419	Girls	Apparel	Topwear	Tops	White	Casual	Gini and Jony Girls Knit White Top	42419.jpg	http://assets.myntassets.com/v1/images/style/p...
1	34009	Girls	Apparel	Topwear	Tops	Black	Casual	Gini and Jony Girls Black Top	34009.jpg	http://assets.myntassets.com/v1/images/style/p...
2	40143	Girls	Apparel	Topwear	Tops	Blue	Casual	Gini and Jony Girls Pretty Blossom Blue Top	40143.jpg	http://assets.myntassets.com/v1/images/style/p...
3	23623	Girls	Apparel	Topwear	Tops	Pink	Casual	Doodle Kids Girls Pink I love Shopping Top	23623.jpg	http://assets.myntassets.com/v1/images/style/p...
4	47154	Girls	Apparel	Bottomwear	Capris	Black	Casual	Gini and Jony Girls Black Capris	47154.jpg	http://assets.myntassets.com/v1/images/style/p...
...	...	...	...	...	...	...	...	...	...	...
2901	51755	Women	Footwear	Shoes	Casual Shoes	Black	Casual	Catwalk Women Black Shoes	51755.jpg	http://assets.myntassets.com/v1/images/style/p...
2902	47630	Women	Footwear	Shoes	Flats	Blue	Casual	Carlton London Women Blue Shoes	47630.jpg	http://assets.myntassets.com/v1/images/style/p...
2903	32836	Women	Footwear	Shoes	Flats	Pink	Casual	Grendha Women Flori Pink Sandals	32836.jpg	http://assets.myntassets.com/v1/images/style/p...
2904	35821	Women	Footwear	Shoes	Heels	Black	Casual	Enroute Women Black Heels	35821.jpg	http://assets.myntassets.com/v1/images/style/p...
2905	18553	Women	Footwear	Shoes	Heels	Blue	Casual	Catwalk Women Mary Janes Blue Flats	18553.jpg	http://assets.myntassets.com/v1/images/style/p...

2906 rows × 10 columns


Distribution of articles SubCategory-wise
Number of products
0
200
400
600
800
1000
1200
Topwear
Bottomwear
Dress
Innerwear
Socks
Apparel Set
Shoes
Flip Flops
Sandal
SubCategory type


Distribution of articles gender-wise
Number of products
0
100
200
300
400
500
600
700
800
Girls
Boys
Men
Women
Gender type

2. Data Preparation

1. Boys' Apparel

- The script creates a subset apparel_boys containing fashion items designed for boys. The condition "Gender=="Boys" filters the DataFrame accordingly.

2. Girls' Apparel

- Similarly, a subset apparel_girls is formed, including fashion items labeled for girls using the condition "Gender=="Girls".

3. Men's Footwear

- The subset footwear_men is generated for men's footwear, filtering items with the condition "Gender=="Men".

4. Women's Footwear

- Lastly, footwear_women is created to encompass women's footwear based on the condition "Gender=="Women".

3. Feature extraction using ResNet

Objectives

- **Feature Extraction**: Utilize a pre-trained ResNet50 model to extract meaningful features from Men's Footwear images.
- **Data Preprocessing**: Employ an ImageDataGenerator to preprocess and augment the input images.
- **Data Directory**: Set up the directory path for the training data, which contains a diverse range of Men's Footwear images.
- **Save Results**: Save the extracted features and corresponding item codes as NumPy arrays for future use.

---

1. Image Dimensions and Directory

- **Dimensions**: The input images are resized to 224x224 pixels to fit the ResNet50 model's requirements.
- **Directory**: The directory path for the training data is specified.

2. Feature Extraction Function

- **ImageDataGenerator**: Images are preprocessed using an ImageDataGenerator with rescaling.
- **ResNet50 Model**: The pre-trained ResNet50 model is loaded without its top layers for feature extraction.
- **Flow from Directory**: A flow of images is generated from the specified directory for processing.
- **Item Codes Extraction**: Item codes are extracted from file names for later reference.
- **Prediction**: Features are predicted using the ResNet50 model.
- **Reshaping**: The extracted features are reshaped for compatibility.
- **Saving**: Features and item codes are saved as numpy arrays for future use.

4. Computing the Euclidean distance and recommending similar products

4.1 Distance computation and Recommendation

Overview

- **Function**: get_similar_products_cnn(product_id, num_results)
- **Input**: Product ID and the desired number of similar products (num_results)
- **Process**:
  - Finds the index of the input product ID in the list of product IDs.
  - Calculates pairwise distances between the input product and all other products using CNN-based feature extraction.
  - Retrieves the indices of the most similar products.
  - Displays the input product image and details.
  - Displays the recommended products along with their details and Euclidean distances from the input image.

Code Breakdown

- **Explanation of key components**:
  - **pairwise_distances**: Utilized to calculate distances between the input product and all other products based on CNN features.
  - **Sorting and selecting**: Using NumPy to identify the most similar products based on calculated distances.
  - **Image and details display**: Leveraging pandas DataFrame to showcase product images and titles.

Example Usage

- **Example input**: Retrieving 5 similar products for the input product ID '13683'.
- Showcase the output with the input product image and details followed by the recommended products and their details along with Euclidean distances.

Visual Representation

- Provide visual representations of the input product and recommended products, emphasizing the role of CNN-based feature extraction in determining similarity.
- Use images of products along with their titles to illustrate the concept.

Key Takeaways

- **Recap the main points**:
  - CNN-based feature extraction for product similarity.
  - Pairwise distances as a measure of similarity.
  - Output format showcasing input and recommended products.

========== input product image ==========

Product Title: ADIDAS Men Adi Quest Blue Sports Shoes

========== Recommended products ==========

Product Title: Fila Men Destiny Grey Sports Shoes
Euclidean Distance from input image: 27.668856

Product Title: ADIDAS Men Silver Phaedra Shoes
Euclidean Distance from input image: 29.393417

Data Loading

- Present the loading of pre-extracted features and corresponding product IDs for different gender categories.
- Emphasize the separation of data for boys' apparel, girls' apparel, men's footwear, and women's footwear.

Data Preparation

- Showcase the conversion of the 'ProductId' column in the 'fashion_df' DataFrame to string type.
- Ensure consistency in data types for effective processing.

Recommender Function

- Present the function get_similar_products_cnn that retrieves similar products based on CNN-based feature extraction.
- Explain how the gender category of the input product determines the choice of pre-extracted features and product IDs.

Function Execution

- Provide an example of how the function is executed.
- Emphasize the determination of the gender category and the subsequent selection of relevant features.

Results

- Illustrate the results with images and details of the input product and recommended products.
- Highlight the calculated Euclidean distance as a measure of similarity.

THANK YOU