

# Project design

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## 1. Scope

### **Domain of the Recommender System**

This recommender system is designed for application within the fashion and e-commerce sectors, with a particular focus on users seeking to purchase apparel they encounter in social media videos on platforms such as TikTok, Instagram, and YouTube. Leveraging computer vision (CV) techniques, the system will analyze images and video frames to extract clothing-related features and suggest visually similar or stylistically complementary products from an online retail database.

The system is intended to serve three primary user groups:

- Social media users interested in identifying and acquiring clothing items worn by influencers or content creators.
- Fashion enthusiasts searching for style ideas and convenient purchasing opportunities.
- E-commerce platforms aiming to boost sales via referrals originating from social media content.

### **User Interface**

The system will present between 5 and 10 recommended products per user query, carefully balancing option variety with cognitive load to prevent decision fatigue while maintaining sufficient diversity in terms of style, price, and availability.

Recommendations will be delivered through a mobile-optimized interface, prioritizing smartphones and tablets as these devices are the predominant means of social media consumption. Key interface features will include:

- Image upload capability (via screenshot or camera capture)
- A scrollable product carousel displaying essential details (price, brand, and purchase link)
- Interactive components such as like/dislike buttons and “see similar” options

### **Mockups & Interaction Design**

Preliminary wireframes will illustrate:

- An image upload interface
- A product carousel featuring 5–10 items, each accompanied by like/dislike buttons

- A feedback pop-up ("Was this helpful? Yes/No"), with simulated user interactions contributing to system data

### **Dynamic Updates and Cold-Start Handling**

The system will retrain weekly to incorporate new feedback and trends. During cold-start situations, it will initially rely on content-based recommendations driven by visual features, gradually integrating collaborative filtering methods as user interaction data becomes available.

### **Business Model**

Revenue will be generated through several streams:

- Affiliate commissions earned from partnered retailers for each completed purchase
- Premium subscriptions offering advanced filtering options (such as eco-friendly items or brand-specific recommendations)
- API licensing opportunities for social media platforms

## **2. Dataset**

The recommender system will primarily utilize the DeepFashion dataset, a publicly available academic resource containing over 800,000 annotated fashion images with detailed attribute labels, including clothing categories, styles, and landmarks. This dataset will support the training of the computer vision components. To improve real-world applicability, additional product data will be collected through targeted web scraping from major e-commerce platforms such as ASOS and Zara, ensuring inclusion of up-to-date inventory and pricing.

Key limitations of the datasets include:

- A significant bias within DeepFashion towards Western-style formal attire
- An absence of natural user interaction data that reflects genuine purchasing behavior
- Potential inconsistencies in product categorization within the scraped e-commerce data

The data will be processed via a standardized pipeline involving:

- Visual feature extraction using a ResNet50 model
- Attribute normalization to manage inconsistent terminology
- Generation of simulated user interaction data for system testing

All data collection and usage activities will adhere strictly to ethical standards:

- No collection of personal or identifiable information
- Compliance with platform terms of service during web scraping
- Exclusive use of all data for academic research purposes

Dataset quality will be evaluated through manual inspection of a random 500-item sample, assessing:

- Accuracy of labels
- Diversity of clothing styles
- Relevance to current fashion trends and market availability

## 3. Method

### **System Architecture**

The recommender system will adopt a modular architecture composed of three principal components: a computer vision module for processing visual inputs, a hybrid recommendation engine combining multiple filtering techniques, and an interactive feedback module. This architecture supports scalable deployment and continuous optimization via user interactions, ensuring both flexibility and efficient system performance.

### **Visual Similarity Module**

The core of the content-based recommendation process is a fine-tuned ResNet50 model, which transforms garment images into 2048-dimensional feature vectors. These embeddings enable precise visual similarity calculations, which are processed using an optimized FAISS index. This setup ensures rapid query responses, typically within 50 milliseconds, providing a real-time user experience.

### **Recommendation Engine**

The system employs an adaptive, two-phase recommendation strategy. In the absence of prior user data (cold start), it relies exclusively on visual content-based recommendations. As user interaction data accumulates, the system progressively incorporates personalized preferences. Final recommendation scores are computed through a weighted combination: 60% visual similarity, 30% individual user preferences, and 10% current popularity trends.

### **Implementation Details**

The system's technical implementation will utilize a Python-based technology stack. PyTorch will support the deep learning modules, while Flask will manage the recommendation-serving infrastructure. PostgreSQL will handle data storage requirements, and FAISS will facilitate efficient vector similarity searches.

Containerization via Docker will ensure consistent deployment across development, testing, and production environments.

## 4. Evaluation

### **Offline Metrics**

The system's performance will be evaluated using held-out data, applying precision@5 and normalized Discounted Cumulative Gain (nDCG) to assess the accuracy of recommendation rankings. These established metrics will measure how effectively relevant items are ranked within the top positions of recommended lists.

### **User Feedback**

A simulated user interface will track implicit feedback via recorded clicks and likes. Additionally, short surveys will collect explicit feedback from users regarding the helpfulness of recommendations.

### **Dynamic Performance**

The impact of weekly model updates will be monitored by comparing system performance metrics before and after retraining. Cold-start scenarios involving newly added items will be evaluated separately to assess initial recommendation quality.

### **Business Impact**

Metrics such as click-through rates and purchase conversion rates will be analyzed to estimate the system's commercial viability, with particular attention to the affiliate marketing revenue model.