**Facial-Fashion Recommendation System Report**

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**1. Approach**

The system recommends fashion items from the Fashion MNIST dataset based on facial attributes extracted from the CelebA dataset. The core approach uses heuristic rules to map specific facial features (e.g., wearing a necktie, lipstick) to clothing categories (e.g., shirts, dresses). This rule-based system prioritizes simplicity and interpretability over complex machine learning models.

**2. Methods Used**

2.1 Data Setup

CelebA Dataset:

* Used facial attributes (Young, Wearing\_Necktie, Eyeglasses, etc.) from list\_attr\_celeba.csv.
* Selected attributes correlating to style preferences (e.g., formal vs. casual).

Fashion MNIST:

* Mapped 10 clothing categories (T-shirts, dresses, coats, etc.) using predefined labels.

2.2 Facial Analysis

a. Heuristic Rules:

#Python code:

if Wearing\_Necktie → Formal → Shirt/Coat

if Wearing\_Lipstick → Dress

if Young + Smiling → Casual → T-shirt/Sneakers

b. Script Workflow:

* Load CelebA attributes.
* Apply rules to assign a Fashion MNIST label.
* Generate recommendations in CSV format.

2.3 Recommendation Logic

* Direct mapping between CelebA attributes and Fashion MNIST categories.
* Output format: [image\_id, fashion\_label, fashion\_category].

2.4 Visualization (Optional)

* Added a script to display CelebA images alongside recommendations.

**3. Challenges Encountered**

3.1 Import Errors:

* Python module resolution issues due to directory structure.
* Fix: Added \_\_init\_\_.py files and adjusted sys.path.

3.2 Path Handling:

* Missing CelebA images due to incorrect file paths.
* Fix: Implemented path validation and error logging.

3.3 Rule Limitations:

* Subjective assumptions (e.g., "male → shirt") may not generalize.
* Limited attribute combinations reduce diversity in recommendations.

3.4 Dataset Mismatch:

* CelebA lacks explicit style labels, requiring manual rule creation.
* Fashion MNIST lacks contextual metadata (e.g., occasion, season).

3.5 Scalability:

* Heuristic rules become unwieldy with more categories.

**4. Suggestions for Improvement**

4.1 Machine Learning Integration

* Method : Supervised Learning
* Description : Train a classifier on labeled CelebA-Fashion pairs
* Benefit : Better accuracy
* Method : CNN-Based Style Detection
* Description : Analyze facial images directly (not just attributes)
* Benefit : Captures nuanced styles
* Method : Clustering
* Description : Auto-discover style groups using unsupervised learning
* Style : Reduces manual rule creation

4.2 System Enhancements

* Hybrid Approach: Combine rules with ML for fallback recommendations.
* Fashion Context: Integrate weather/occasion data (e.g., winter → coats).

4.3 Technical Improvements

* Error Handling: Add retry logic for missing images.
* Parallel Processing: Speed up CSV generation for large datasets.
* Dynamic Rules: Load rules from a config file for easy updates.

**5. Conclusion**

The current system provides a functional baseline for style recommendations using simple heuristic rules. While effective for small-scale applications, transitioning to machine learning and addressing dataset limitations would significantly enhance relevance and scalability. Future work should focus on collecting labeled data and implementing adaptive recommendation algorithms.

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