Key Considerations Influencing Recommendations

In a collaborative filtering model, several key factors influence the generation of recommendations. These considerations are essential for understanding why specific products are recommended to users. Below is a detailed explanation of the factors influencing recommendations.

1. Customer-Product Interaction History

The model uses the interaction history between customers and products as the foundational data. This can be implicit feedback, such as how often a customer has bought a product, or explicit feedback like ratings. In this case, higher interaction counts (such as purchases) signal stronger customer preference for certain products.

2. Latent Factors (Hidden Preferences)

Latent factors are extracted using techniques like Singular Value Decomposition (SVD). These factors represent hidden patterns or preferences that are not directly observable. For instance, one latent factor might capture a preference for luxury items, while another might capture a preference for seasonal products.

3. Customer-Product Similarities (Collaborative Filtering)

Collaborative filtering finds similarities between customers or products. For example, if two customers have purchased similar items, the model will likely recommend to one customer products that the other has bought. Similarly, if a product is similar to another product that a customer has bought, it might be recommended.

4. Unseen Products (Products Not Yet Purchased)

The model recommends products that the customer has not yet interacted with. Based on patterns from similar customers and products, the model calculates the likelihood that a customer will purchase a new product and makes recommendations accordingly.

5. Top-N Recommendations (Ranking of Predictions)

After predicting interaction scores for each product, the model ranks them for each customer. The top N products with the highest predicted interaction scores are recommended. These are the products that the model believes the customer will most likely engage with.

6. Global Patterns in Data (Collaborative Filtering)

The model captures global patterns across all users and products. For instance, if a product is popular across many users, the model might recommend it to users who have not yet purchased it. Similarly, relationships between different categories or complementary products can also influence recommendations.

7. Balance of Exploration and Exploitation

The model balances exploitation (recommending products similar to what the customer already likes) and exploration (introducing new, unseen products). By learning from patterns in the data, the model ensures a mix of familiar and new products in the recommendations.