COMP9727 Project Design Report

Furniture Recommendation - Based on IKEA Furniture

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1 Scope

1.1 Use Cases

Domain Positioning: This project focuses on a high-end customized furniture recommendation system, avoiding common FMCG e-commerce recommendation fields. Recommendations in this scenario are highly contextual, involve low-frequency decision-making, and high-value transactions, requiring the system to have fine-grained understanding of user preferences and scene matching capabilities.

Target User Group: Mainly middle to high-income groups aged 25 to 45, who have strong consumption capacity and aesthetic pursuit, and are important consumption mainstays in the home furnishing market. Their main behaviors include overall decoration after first-time home purchase, secondary decoration, and local space upgrading.

Recommendation Interaction Mode: Users will be guided to complete a style preference test - a personalized questionnaire lasting about 5 minutes - upon first login, and the system will build an initial user profile based on this. On the main interface, the system will recommend 6-12 pieces of furniture based on this profile, balancing content diversity and user cognitive load.

User Interface Presentation: The recommendation system is deployed in a responsive web application with good cross-device compatibility for desktop and mobile ends. The page supports 3D furniture model rotation and preview, enhancing users' perception and judgment of products. This design also provides an operable interaction prototype for subsequent user research.

1.2 Interaction and Feedback Collection

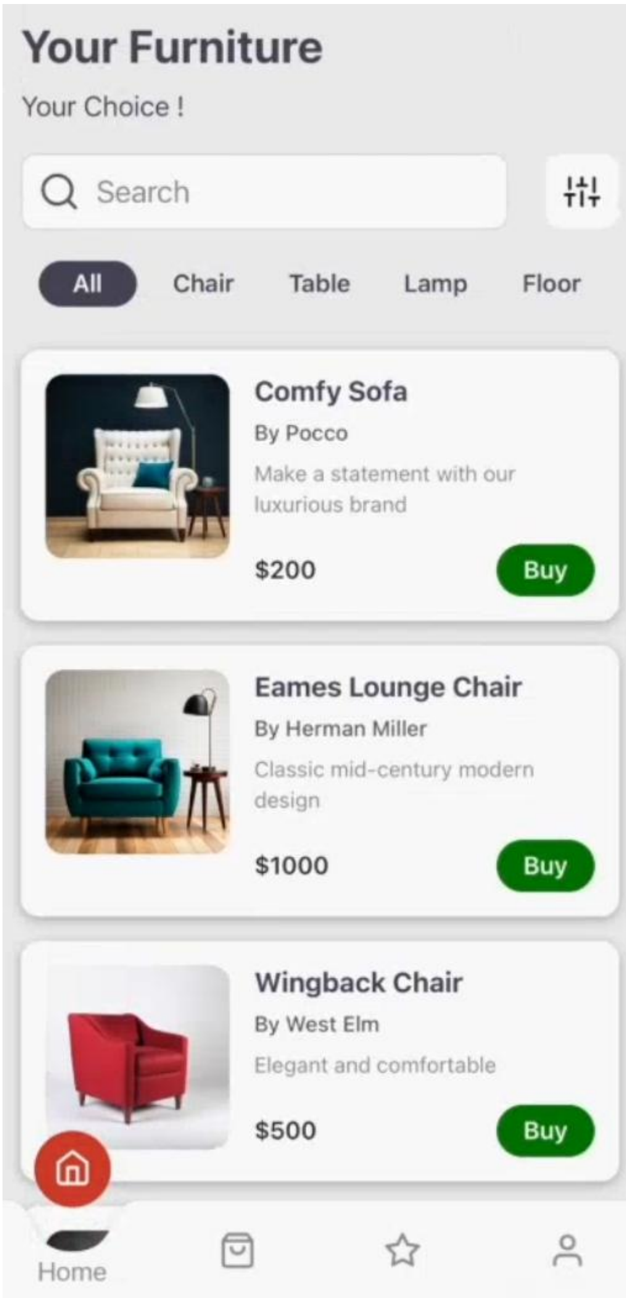
The system captures user feedback through a multi-level interaction mechanism:

Basic Feedback Mechanism: Users can select "Like", "Skip", or "Already Owned" for each recommended furniture item, used to update user profiles and preference models.

Deep Interaction Module: Provides a virtual room designer, allowing users to drag and drop recommended furniture into room models and receive real-time feedback scores based on style compatibility analysis, thus promoting two-way learning between users and the system.

Regular Feedback Mechanism: The system pushes personalized short questionnaires weekly to obtain fine-grained feedback on recommended content, such as "Did you like the color matching in the recommendation?". This mechanism helps continuously optimize recommendation effects and alleviate cold start issues.

1.3 Mobile Interface



1.4 Business Model

Commission-based Shopping Guide: When users click on recommended furniture and jump to cooperative brand e-commerce platforms, if a transaction is completed, the platform will obtain a 15% recommendation commission, constructing a clear business closed loop.

Data Services: Based on the aggregated analysis of user feedback, matching preferences, and style tags, generate quarterly furniture trend reports and sell them to brand parties for new product development and market insights.

1.5 Cold Start

User Cold Start: Initialize the profile with a style questionnaire and combine it with popular matching packages for the first few rounds of recommendations to quickly establish an interest connection with users.

Product Cold Start: For new furniture products without user interaction, vectorize them through content label similarity (such as material, style, and usage space) and incorporate them into the content recommendation module.

1.6 Model Update

The collaborative filtering model is incrementally updated daily, and parameter tuning for SVD/SVD++ is completed using the Surprise library.

The graph neural network model is fully reconstructed monthly based on the user behavior graph, and model iteration and optimization for GAT or GraphSAGE are completed with PyTorchGeometric.

2 Datasets

2.1 Data Source

We adopted the IKEA Furniture dataset from the Kaggle platform. The key fields of the dataset are introduced as follows:

name: The commercial name of the product.

category: The furniture category to which the product belongs (sofa, bed, chair, trolley, ...).

Price: The current price.

old_price: The product price before the discount.

Short_description: A brief description of the item.

full_Description: A very detailed description of the item.

designer: The name of the designer who designed the item, extracted from the full_description column.

sellable_Online: Whether the product is available for online purchase or only in physical stores (Boolean value).

other_colors: If the item is available in other colors, or if only one color is displayed on the website (Boolean value).

Among the above fields, full_Description, Short_description, Price, and category fields have a greater impact on the recommendation model.

2.2 Data Quality

Dataset Advantages:

Good data integrity: From the provided data, most fields have values, and there is no obvious missing field situation. Each product has a name, category, picture link, purchase link, rating, number of reviews, and price information.

High data richness: It contains information from multiple dimensions, such as basic product attributes (name, category, picture link), user feedback (rating, number of reviews), and price information (discounted price, actual price), which can meet various analysis needs.

Limitations:

Limited data fields: Although some basic information is included, it may not be sufficient for more in-depth analysis. For example, it lacks detailed attributes such as the brand information, size specifications, and material description of the product.

Insufficient data depth: For some analysis scenarios, such as market trend analysis or consumer behavior analysis, more contextual information may be needed, such as the inventory status of the product, sales rankings, details of promotional activities, etc., which are not provided in this dataset.

Coarse data granularity: The dataset provides product-level information, but for some analysis needs (such as user behavior analysis), more fine-grained data may be required, such as user purchase behavior, browsing records, etc., which are not available in the current dataset.

Countermeasures: We plan to generate fictional rating data based on reasonable assumptions by synthesizing user interaction logs; at the same time, collect furniture matching image tag data from sites such as Pinterest to build a knowledge graph to enhance recommendation effects.

2.3 Data Usage Scheme

Purpose	Model Adaptation	Fields/Methods Used
Collaborative filtering training	SVD/SVD++ (Surprise)	user_id + item_id + rating
Content recommendation	TF-IDF	name, style, material
Matching modeling	Graph Neural Network (PyG)	Build furniture style/space matching graph

2.4 Data Preprocessing Flow

3 Recommendation Methods

We comprehensively consider the different stages and target requirements of the recommendation system in the furniture scenario, design the following three types of models, and adopt a weighted fusion strategy:

Method	Applicable Scenario	Advantages	Challenges
Content filtering	Cold start for new users/products	Realize personalization using product attributes	Difficult to capture user contextual matching preferences
Collaborative Filtering (SVD++)	Stable user stage	Mine implicit interests and similar user preferences	Sparsity affects effectiveness
Graph Neural Network (GNN)	Furniture matching recommendation	Model the style compatibility and combinability between furniture	High training and inference overhead

Content Filtering: As a standard technical approach to handle "cold start" problems, it is particularly suitable for recommending items of interest to users when there is a lack of historical user behavior data. High-end furniture itself has significant style features, material attributes, and usage scenarios, making it very suitable for building a structured content vector model. We will perform TF-IDF vectorization on text fields such as furniture names, styles, and materials, and complete initial recommendations by calculating the similarity between user preference vectors and product vectors.

Collaborative Filtering: Especially the matrix factorization-based SVD++ model, is one of the core methods of industrial recommendation systems. SVD++ can integrate user ratings (explicit feedback) and implicit feedback (such as browsing, clicking, collecting) information to more accurately depict user interests. We plan to train this model by constructing simulated interaction data (such as synthetic rating logs).

Furniture Matching Recommendation: It involves not only users' preferences for individual items but also emphasizes the combination adaptability between products. Traditional collaborative filtering or content filtering methods are difficult to capture the structural, matching, and combinational relationships between furniture. Therefore, we introduce Graph Neural Networks (GNN) to model the compatibility of style, function, and spatial layout between furniture products.

Fusion Strategy

Final recommendation score = 0.3 × content similarity + 0.4 × collaborative score + 0.3 × GNN compatibility score

This approach balances short-term and long-term preferences, as well as cold start processing capabilities and matching recommendation accuracy.

Technology Stack

Surprise (SVD++)

Sklearn + TF-IDF (content vectorization)

PyTorchGeometric (graph neural network)

Table 1: Time Planning and Milestones

Stage	Time	Deliverables
Data Preprocessing	Weeks 1-2	Cleaned dataset + knowledge graph
Content Filtering Implementation	Week 3	Style-based cold start recommendation module
Collaborative Filtering Implementation	Weeks 4-5	SVD++ model (Surprise)
GNN Matching Model	Weeks 6-7	PyG-implemented furniture compatibility network
Hybrid Recommendation Integration	Week 8	Weighted fusion API
User Simulation Test	Week 9	Questionnaire feedback report + indicator comparison

4 Evaluation

4.1 Offline Indicators

Indicator	Meaning	Target
Precision@6	Proportion of Top-6 recommendations	≥0.6

	matching user preferences	
Coverage@100	Proportion of different products the system can recommend	≥0.3
Style Consistency Score	Experts' rationality score (1-5 points) for recommended matching	Average ≥4.0

Precision@6: The number of recommendation slots on the homepage is limited (6-12), so it is necessary to ensure high-quality hits on user interests. Precision is the most intuitive indicator to measure accuracy, especially suitable for scenarios where users use it for the first time or there are few recommendation slots.

Coverage@100: Used to measure whether the system only recommends popular/head products. Especially when furniture products have style/function diversity, the recommendation system needs to have the ability to "discover" non-mainstream matches or new styles.

Style Consistency Score: Furniture recommendation is different from individual item recommendations such as books and movies. It emphasizes the beauty and logic of "complete set matching". Manual annotation is an effective way to capture subjective aesthetic feedback, making up for dimensions that the model hard to measure.

4.2 Online User Research

Simulation Process:

Recruit users: 20 people in the target group, covering both male and female users.

Task design: Use Figma high-fidelity prototypes to complete 1 room matching task.

Recommendation frequency: The system automatically recommends furniture 5 times, and users can adjust and rate it.

Feedback Acquisition:

Scale questionnaire: SUS system usability scale (out of 100), recommendation satisfaction scale (1-5 points).

Open-ended interview: Guide users to describe "which recommendations did you unexpectedly like".

Evaluation Objectives:

Satisfaction ⩾4.0 and SUS ⩾70 are the qualified standards for the system.

4.3 Resources and Scalability

Realtime Performance: Collaborative filtering recommendations preload vectors, with response time controlled within 500ms.

Training Cost: The full training cost of the graph neural network is controlled within 4 hours, using AWS p3.2xlarge-level GPU nodes.

Expansion Capability: The system supports heterogeneous product input and incremental learning in the case of continuous increases in products and users.

5 Conclusion and Feasibility

5.1 Technical Feasibility

The project team has a multidisciplinary background, covering the following capabilities:

Recommendation algorithms: Proficient in using Surprise and Sklearn.

Deep learning modeling: Master PyTorch and PyG.

User research and interaction design: Have HCI design experience and prototype construction capabilities.

5.2 Innovation Guarantee

Focus on the high-end furniture niche market and avoid conventional e-commerce recommendation scenarios.

Build a knowledge graph to assist graph neural networks and improve recommendation depth and interpretability.

Introduce virtual matching interaction and fine-grained user feedback mechanisms to enrich user research dimensions.

5.3 Risks and Countermeasures

Data Sparsity: Adopt synthetic behavior + knowledge graph enhancement.

High Model Complexity: Collaborative filtering uses incremental updates, and GNN uses efficient SGD optimization and graph sampling methods to reduce computational overhead.

Limited User Research Samples: Adopt multi-round experiments and task-based guidance to improve data reliability.