

**MACHINE-LEARNING-BASED PRODUCT ASSORTMENT RECOMMENDATION FOR RETAIL OUTLETS IN DISTRIBUTION: CROSS-SELL AND ASSORTMENT-WIDTH GROWTH (CONCEPTUAL MODEL)**

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**ANNOTATSIYA**

Agent yoki van-seller savdo nuqtasiga borganda muhim qaror — do'kon hali sotmayotgan, lekin sotishi ehtimoli yuqori mahsulotni taklif qilish (cross-sell), shu orqali assortiment kengligi va o'rtacha buyurtmani oshirish. Uch qismli turkumning yakunlovchi qismida har bir savdo nuqtasiga mahsulot tavsiya qilish uchun mahsulotlararo (item-item) o'xshashlikka asoslangan market-basket usulining konseptual modeli taklif etiladi va ommaboplikka asoslangan bazaviy usul bilan solishtirish metodologiyasi (Precision@k, Recall@k) bayon qilinadi.

**Kalit so'zlar:** mahsulot tavsiyasi, market-basket, item-item o'xshashlik, cross-sell, assortiment kengligi, MSL, FMCG.

**АННОТАЦИЯ**

Когда агент или ван-селлер приходит в торговую точку, важное решение — предложить товар, который точка ещё не продаёт, но с высокой вероятностью примет (cross-sell), повышая тем самым широту ассортимента и средний заказ. В заключительной части цикла из трёх работ предлагается концептуальная модель рекомендации товаров для каждой торговой точки на основе межтоварной (item-item) близости (market-basket) и описывается методология сравнения с базовым методом по популярности (Precision@k, Recall@k).

**Ключевые слова:** рекомендация товаров, market-basket, item-item близость, cross-sell, широта ассортимента, MSL, FMCG.

**ABSTRACT**

When an agent or van-seller visits an outlet, an important decision is to offer a product that the outlet does not yet sell but is likely to accept (cross-sell), thereby increasing assortment width and the average order. The concluding part of this three-part series proposes a conceptual model for recommending products to each outlet based on item-item similarity (market-basket) and describes the methodology for comparison with a popularity-based baseline (Precision@k, Recall@k).

**Keywords:** product recommendation, market-basket, item-item similarity, cross-sell, assortment width, MSL, FMCG.

## INTRODUCTION

In FMCG distribution, success depends on a product's availability at the outlet: if a shop does not stock a product, it cannot sell it. Expanding the assortment at each outlet (range selling) and offering the right product are important sources of sales growth. A field representative cannot keep hundreds of product-outlet combinations in mind; this article proposes a conceptual recommendation model that answers the question "which new product should be offered."

## LITERATURE REVIEW

Recommender systems have been studied for decades. Agrawal and Srikant [1] proposed algorithms for mining association rules — products that are purchased together. Sarwar and colleagues [2] introduced item-item collaborative filtering, recommending on the basis of "similar items," and Linden and colleagues [3] described such a system deployed at Amazon.com. Koren, Bell and Volinsky [4] advanced the field with matrix-factorization (latent-factor) techniques, which proved superior to classic nearest-neighbor methods in the Netflix Prize. Ricci, Rokach and Shapira [5] consolidated the principal methods of recommender systems in a comprehensive handbook. In the FMCG context, these ideas connect to the must-stock list (MSL) and category management, where machine learning is increasingly applied [6, 7].

## PROBLEM STATEMENT AND DATA SCHEMA

There are  $N$  outlets and  $M$  products; the current assortment of each outlet is known (Figure 1). The task is to rank the products that an outlet does not yet stock but is likely to accept, and to recommend the top- $k$  of them. This assortment and order data is based on the fields available in SalesDoctor [10], a real DMS/SFA platform widely used in Uzbekistan.

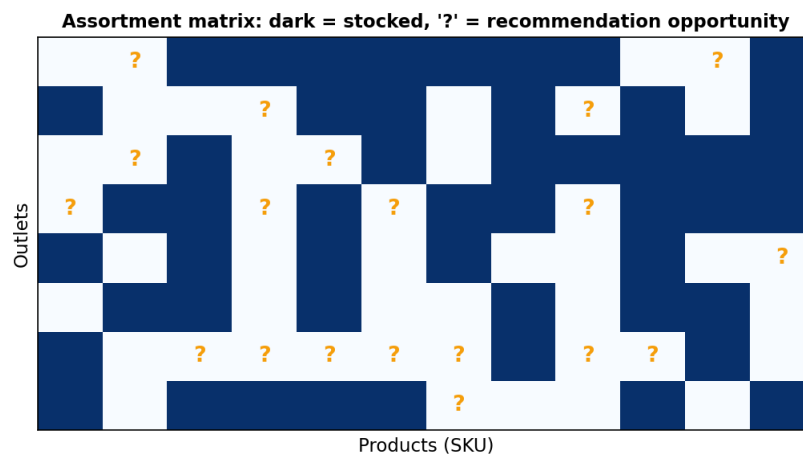


Figure 1. Assortment matrix: dark = the outlet stocks the product, '?' = a recommendation opportunity (gap).

## PROPOSED METHODOLOGY

### *Item-item similarity and recommendation*

Inter-product similarity is computed over the assortment matrix using cosine similarity: products that are stocked together in many outlets are considered similar, building on item-based collaborative filtering [2, 3]. For each outlet, the products it does not stock are scored by their

similarity to its current basket, and the top-k are recommended; this is compared with a popularity baseline (Figure 2). As an alternative, latent-factor (matrix-factorization) models [4] can capture more complex co-occurrence patterns.

Product recommendation concept: market-basket vs popularity (Module 3)

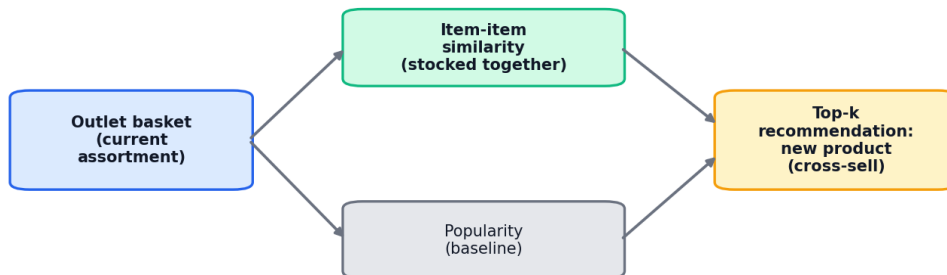


Figure 2. Product recommendation concept: market-basket versus popularity baseline.

**Cold start and extensions**

For a newly opened outlet or a new product (NPD), history is lacking — the “cold-start” problem. To mitigate it, the item-item method is combined with content-based signals (outlet type, region, product category) in a hybrid approach [5]. Moreover, weighting recommendations by business criteria — product margin, the must-stock list (MSL), and the return/defect rate — increases practical value; a learning-to-rank model (for example, gradient boosting [9]) can combine these signals.

**Integration into the unified system**

When combined with the previous modules of the series, the field representative obtains, for each visit, a complete plan: whom to visit, how much, and what to offer (Figure 3). The recommendation is naturally linked to the demand forecast [8].

Architecture of the proposed unified decision-support system

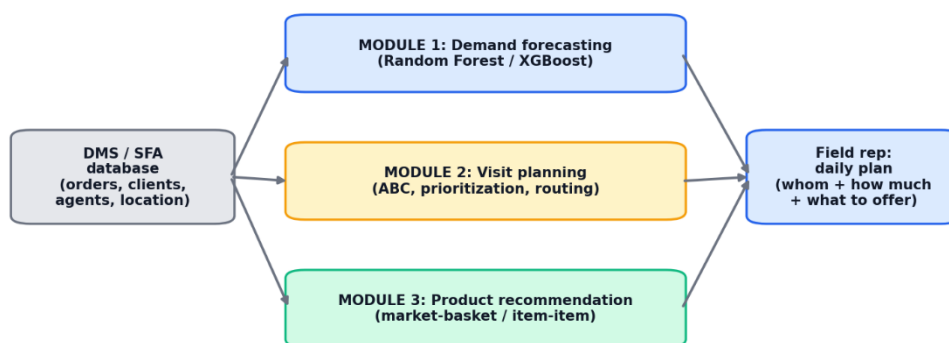


Figure 3. Integration of the three modules into a unified decision-support system.

**EVALUATION METHODOLOGY**

Recommendation quality is evaluated on a time-based split using the following metrics (Table 1): the accuracy and coverage of the top-k recommendations, and the lift over a baseline method.

Table 1. Evaluation metrics for the recommendation system (definitions)

Metric	Formula	What it measures
Precision@k	correct recommendations / k	accuracy of the top-k recommendations
Recall@k	matches found / all relevant	coverage
Lift	system accuracy / baseline accuracy	improvement over the baseline

**Note:** offline evaluation compares the recommendations against the products an outlet actually adopted in the next period; online evaluation additionally measures the acceptance rate and the effect on assortment width and average order value.

### EXPECTED RESULTS AND DISCUSSION

According to the literature, item-item collaborative filtering is expected to outperform a popularity-based baseline because it accounts for outlet-specific affinities [2, 3]: a product that “similar outlets stock together” may suit a given outlet even if it is not broadly popular. This targets numeric distribution and average order value. Concrete quantitative results are to be obtained on real data.

### PRACTICAL SIGNIFICANCE

Integrated into the field-representative (SFA) application, the system provides each outlet with a concrete list of “additional products to offer.” This aims to increase numeric and weighted distribution, assortment width (SKUs per outlet), and average order value, while tailoring the assortment to each outlet’s profile. The system learns from the representative’s response (accepted/rejected) and improves over time. Together, the three modules — demand forecasting, visit planning, and product recommendation — form a single, data-driven platform for managing the field force.

### LIMITATIONS AND FUTURE WORK

The item-item method is subject to the cold-start problem and does not, by itself, account for price, margin, shelf life, or credit limits. Future work includes hybrid methods (content + collaborative), a margin-aware objective function, incorporating the return rate into the recommendation, and testing the model on real data.

### CONCLUSION

This article proposed an item-item similarity-based conceptual model for recommending product assortment to retail outlets, and described its evaluation methodology. At the close of the three-part series, demand forecasting, visit planning, and product recommendation combine into a single, data-driven management system that is ready for empirical verification on real data.

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