Scheme Recommendation using Linear Programing Optimization

# 1. Methodology

🔹 Step 1: Product Recommendation Using Similarity

- Approach: Cosine similarity-based collaborative filtering.  
- Inputs: Binary user-product matrix showing whether a partner purchased a product.  
- Output: Top 3 product recommendations per partner based on user similarity.

🔹 Step 2: Scheme Recommendation via Linear Programming (LP)

- Approach: Scheme recommendation as a Linear Optimization problem.  
- Goal: Maximize scheme allocation for top products under constraints like partner type, region, and growth potential.  
- LP Constraints:  
 - Scheme budget limits.  
 - Scheme-product compatibility.  
 - Business rules for pairing schemes (e.g., no overlap between discount-heavy schemes).

🔹 Step 3: Mapping Recommendations

- Final Output: Mapped top product recommendations to optimal scheme combinations: Scheme\_1, Scheme\_2, Scheme\_3.

# 2. Key Findings and Business Insights

- Bulk Purchase and Loyalty are the most frequently recommended schemes.  
- Partners like 001\_3 and 002\_79 are highly similar to others and receive consistently strong scheme allocations.  
- Products like RMU and ACB appear across many top optimized recommendations due to high similarity and historical success.  
- The LP model provides balanced scheme distribution tailored to business goals and region-wise preferences.

# 3. Assumptions

- Partner purchase history is binary (purchase or not).  
- All products are assumed to have equal weight in similarity calculations.  
- Scheme effectiveness is uniform across geographies (unless explicitly modeled).  
- LP assumes availability of enough budget to allocate 3 schemes per product.

# 4. Limitations

- No pricing or sales quantity incorporated into scheme selection.  
- Temporal factors (e.g., seasonality, campaign duration) are not modeled.  
- Cold-start partners (new stockists) are handled using fallback logic, not similarity or LP.  
- Real-world constraints (e.g., delivery limitations, logistic issues) are not considered in LP optimization.

# 5. Edge Cases

- Partners with no purchases → fall back to top popular products + fixed scheme suggestions.  
- Products with low purchase frequency → may not get enough matches, hence dropped in LP optimization.

# 6. Reference Links

https://scikitlearn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine\_similarity.html  
https://coin-or.github.io/pulp/  
https://towardsdatascience.com/collaborative-filtering-recommender-systems-d9b75a9dcb49