Final Scheme Recommendation System

# 1. Methodology

## A. Combined Recommendation Pipeline

Goal: Recommend optimized promotional schemes for each partner-product pair based on product relevance and partner profile.  
Method:  
- A hybrid collaborative filtering approach is used where products are recommended to partners using cosine similarity.  
- For each recommended product, the most effective schemes are identified based on similar partner behaviors and past scheme applications.  
- Final output includes: Product recommendations, Similarity scores, and Top 3 Scheme recommendations (Scheme\_1, Scheme\_2, Scheme\_3).

## B. Optimization Layer

- The scheme selection is optimized based on contextual factors such as product price, stockist type, and purchase tendency.  
- Schemes like 'Discount', 'Bulk Purchase', and 'Loyalty' are tailored based on historical impact on sales growth and engagement metrics.  
- This allows personalized and impactful partner engagement at scale.

# 2. Key Findings & Business Insights

Multi-Scheme Strategy:  
- Combining multiple schemes per product increases engagement chances across diverse partner profiles.  
  
Discount Sensitivity:  
- Products like 'RMU' and 'VCB' showed higher affinity for Discount-based schemes in low growth regions.  
  
Partner Segmentation:  
- Loyalty schemes worked best with repeat buyers, while Bulk Purchase schemes were effective among high-volume wholesalers.  
  
Product-Partner Matchmaking:  
- The cosine similarity method accurately grouped partners with similar product affinity, improving the relevance of scheme recommendations.

# 3. Assumptions, Limitations & Edge Cases

Assumptions:  
- Scheme effectiveness is inferred based on similarity of partner behavior, not directly from transactional outcome.  
- Product purchase history is a valid proxy for future intent.  
- Scheme application is assumed to be independent of external marketing efforts.  
  
Limitations:  
- No A/B testing or causal validation of scheme success.  
- Cold start problem persists for new partners with no historical data.  
- No real-time dynamic pricing or campaign alignment.  
  
Edge Cases:  
- Partners with sparse product history may get generic or less optimal recommendations.  
- Similarity scores across unrelated partners can introduce noise in scheme mapping.  
- Fixed scheme categories (e.g., scheme1, scheme2) may not adapt to evolving market dynamics.

# 4. Reference Links

https://scikitlearn.org/stable/modules/generated/sklearn.metrics.pairwise.cosine\_similarity.html  
- https://towardsdatascience.com/product-recommendation-system-in-python-d8f4f173fca5  
- https://www.analyticsvidhya.com/blog/2021/06/build-your-own-recommendation-system-using-python/