Enhancing Mutual Fund Recommendation System Using Modern Portfolio Theory: A Multi-Model Approach

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Objective of this study

- Develop a mutual fund recommendation system with following goals:
    1. Personalize recommendations to align with investor risk profiles and enhance overall satisfaction (utility).
    2. Achieve High Performance on standard evaluation metrics, including:
        - Precision@K
        - Normalized Discounted Cumulative Gain (NDCG@K)

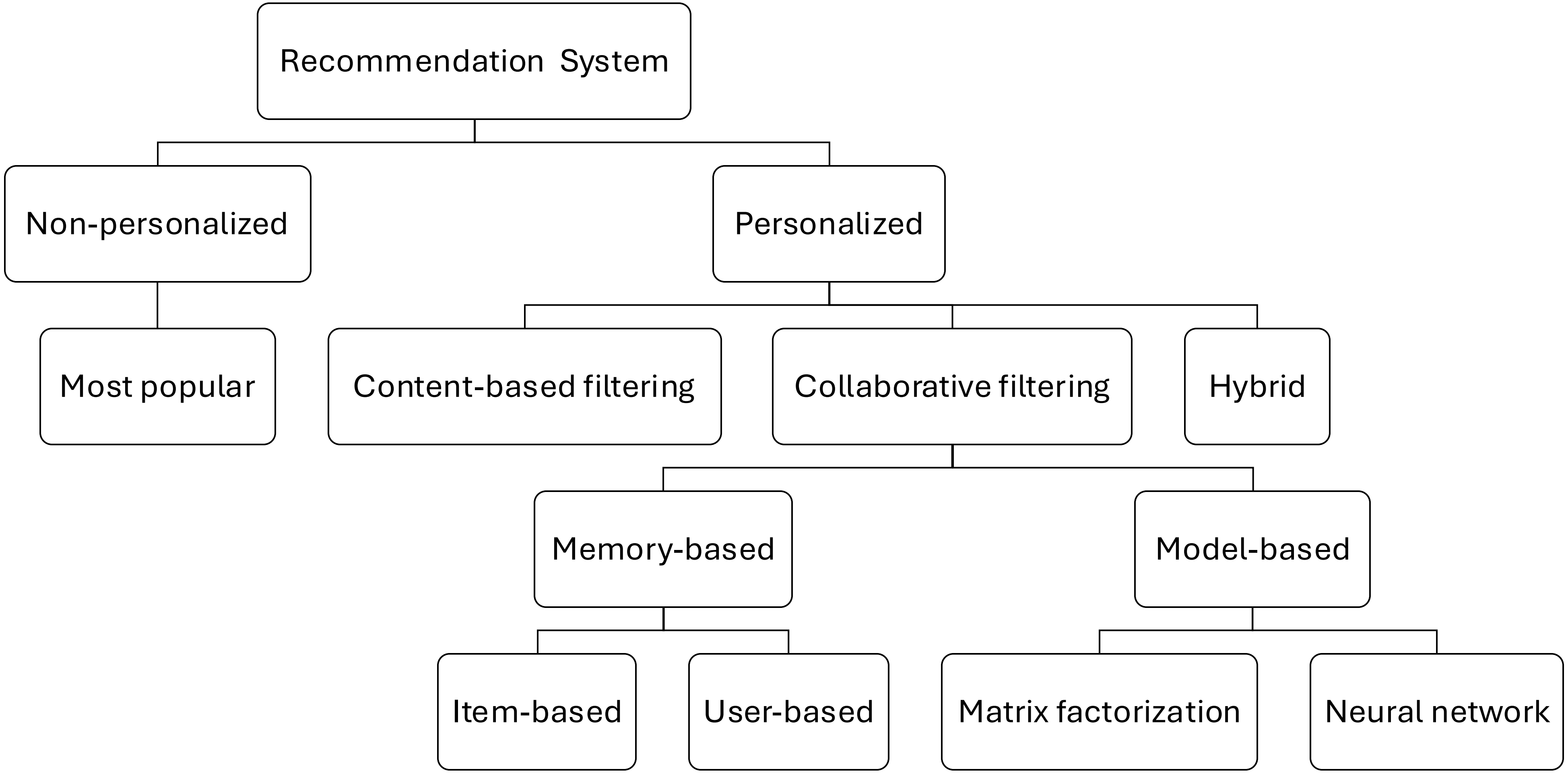
Modern Portfolio Theory (MPT)

- Modern Portfolio Theory (MPT) is a widely recognized framework for optimizing investor portfolios (Pfaff, 2016). It aims to maximize expected return of a portfolio for a given amount of risk, or minimize risk for a target level of return.
- (Patel & Subhodeep, 2017) The theory was originally proposed by Harry Markowitz in 1952, revolutionizing the way investors approached portfolio construction. (Patel & Subhodeep, 2017)
- In reality, individual investors look to maximize their future utility of wealth, not their future wealth (Berns, 2020). Investors will construct portfolios that achieve a superior risk-return profile compared to holding individual assets in isolation.

Recommendation system

- Recommendation systems are essential tools designed to suggest relevant items to users, playing a critical role in enhancing user experience.
- Type of recommendation system can be categorized into three main types: content-based, collaborative filtering and hybrid (Singhal et al., 2017).
    1. Content-based recommendations focus on attributes of items to find similar items.
    2. Collaborative filtering recommendations are based on users' past behavior and preferences to find items that similar users have liked. Mostly used in movies, books, and music (Ashish et al., 2017).
    3. Hybrid systems combine strengths of content-based and collaborative filtering to create better recommendations (Singhal et al., 2017).

Types of recommendation system



Proposed system

- **Modern Portfolio Theory (MPT):** Markowitz framework optimize portfolio allocation tailored to each investor's level of risk, but it suffer from lack of personalization unlike standard recommendation system.
- **Collaborative filtering (CF):** It very popular for personalized recommendations, but in the context of financial assets, it often fails to account for users' risk preferences, and the complexity of the results can be a challenge (Su & Khoshgoftaar, 2009).
- To overcome this limitation, we propose *"Enhancing Mutual Fund Recommendation System Using Modern Portfolio Theory: A Multi-Model Approach"* that leverages modern portfolio theory and machine learning to provide personalized mutual fund recommendations.

Calculation steps of proposed system

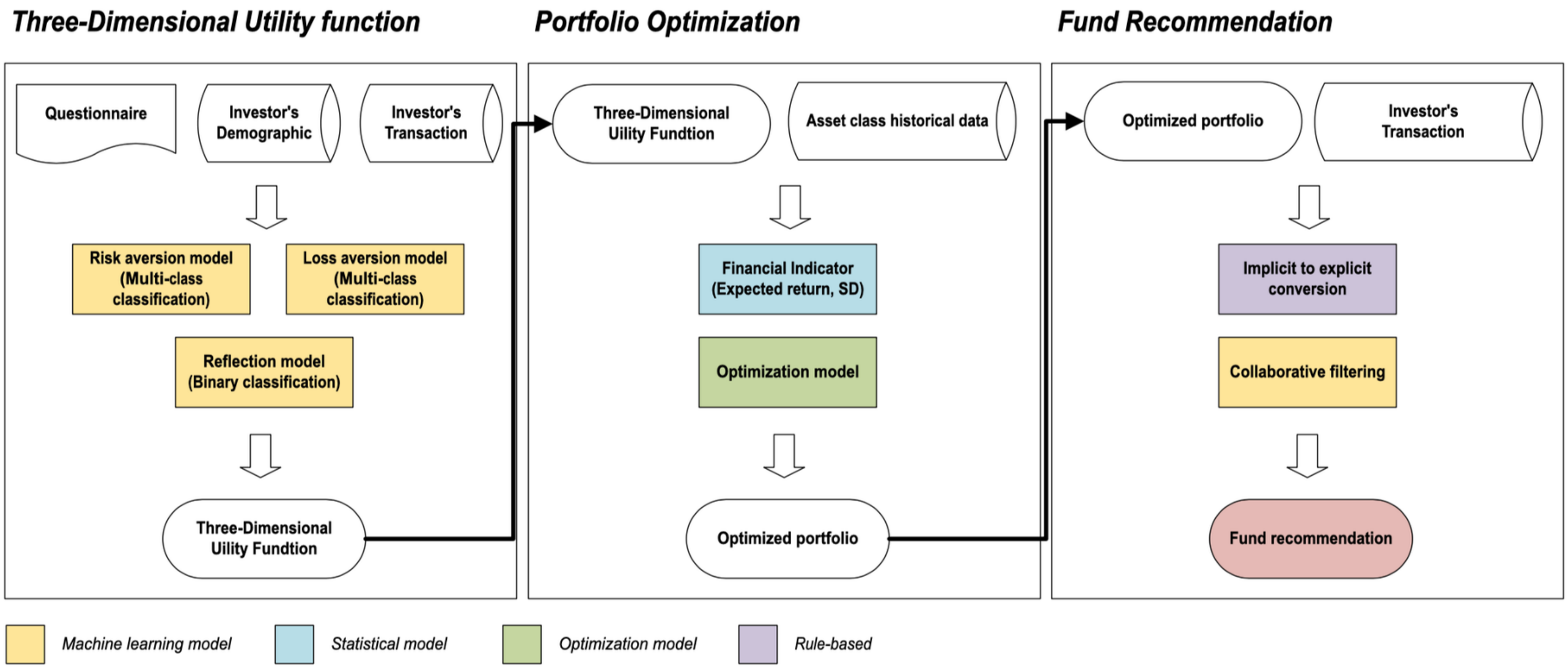
1. **Three-Dimensional Risk Profile Utility Function:** Predict a customer-specific utility function for risk aversion, loss aversion, and reflection effects using profile data (e.g., demographics, transactions, interactions).
2. **Portfolio Optimization:** Align asset classes with customer's risk profile by analyzing metrics like expected return, variance, kurtosis, and skewness, optimizing allocation weights to maximize utility.
3. **Collaborative Filtering:** Apply collaborative filtering to rank and identify top N products based on customer's behavior and preferences.
4. **Final Recommendation:** Deliver top N products by integrating asset class mapping and optimized weights, ensuring relevance and alignment with the risk profile.

Three-dimensional risk profile utility function

Parameter	Behavior	Example Action
Risk Aversion (γ)	Avoids high-risk mutual funds, even if expected return is higher.	Prefers bond mutual funds or balanced funds with lower volatility.
Loss Aversion (λ)	Focuses more on avoiding losses than achieving gains.	Holds on to underperforming funds, hoping for recovery instead of reallocating to better options.
Reflection (ϕ)	Switches between risk-averse and risk-seeking behavior based on whether portfolio shows gains or losses.	Locks in profits during gains but takes excessive risks during losses to avoid realizing them.

$$U = \begin{cases} 2 - W^{(1-\gamma)} \; for \; r \geq 0 \\ 2 - \lambda \; W^{(1-\gamma)} \; for \; r < 0, \varphi = 0 \\ 2 + \lambda \; (2 - W)^{(1-\gamma)} \; for \; r < 0, \varphi = 1 \end{cases}$$

System diagram



How machine learning improve MPT (1)

Limitation of traditional method:

- Traditional methods for creating three-dimensional utility functions rely on questionnaires, which are not scalable for a large group of investors.

Use machine learning:

- Define utility function as $U(\ .\ ) = f(\gamma\ ,\ \lambda\ ,\ \phi)$.
- Collect data for γ, λ and ϕ through questionnaires.
- Perform feature engineering on observed group and train a predictive model on collected data to predict risk profiles for others investor.
    1. γ (Risk aversion parameter): Multi-class classification
    2. λ (Loss aversion parameter): Multi-class classification
    3. ϕ (Reflection parameter): Binary classification

How machine learning improve MPT (2)

Limitation of traditional method:

- Markowitz framework optimizes portfolio allocation based on each investor's risk level but lack of personalization.

Use machine learning:

- After optimizing each asset class weight to maximize a three-dimensional risk profile utility function, specific products are still not being recommended.
- Use collaborative filtering to rank funds that investors might interest.
- Assign recommended fund to individual investors based on their optimized asset class weights.
- Send personalized fund recommendation to individual investor.

Optimized portfolio on various parameters

$\lambda = 1$, $\varphi = 0$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	81%	53%	33%
Real Estate - Domestic - Passive	0%	0%	0%
Duration - Domestic - Passive	19%	38%	30%
Commodities - Passive	0%	9%	9%
Equities - Domestic - Div. l/s ARP	0%	0%	28%

$\lambda = 1$, $\varphi = 1$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	100%	100%	100%
Real Estate - Domestic - Passive	0%	0%	0%
Duration - Domestic - Passive	0%	0%	0%
Commodities - Passive	0%	0%	0%
Equities - Domestic - Div. l/s ARP	0%	0%	0%

$\lambda = 1.5$, $\varphi = 0$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	38%	30%	24%
Real Estate - Domestic - Passive	0%	0%	0%
Duration - Domestic - Passive	34%	28%	24%
Commodities - Passive	9%	8%	8%
Equities - Domestic - Div. l/s ARP	19%	34%	44%

$\lambda = 1.5$, $\varphi = 1$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	53%	51%	50%
Real Estate - Domestic - Passive	1%	3%	11%
Duration - Domestic - Passive	35%	33%	25%
Commodities - Passive	11%	13%	14%
Equities - Domestic - Div. l/s ARP	0%	0%	0%

$\lambda = 3$, $\varphi = 0$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	20%	19%	18%
Real Estate - Domestic - Passive	0%	0%	0%
Duration - Domestic - Passive	20%	20%	19%
Commodities - Passive	6%	6%	6%
Equities - Domestic - Div. l/s ARP	54%	55%	57%

$\lambda = 3$, $\varphi = 1$

	$\gamma = 3$	$\gamma = 6$	$\gamma = 12$
Equities - Domestic - Div. LO ARP	21%	21%	21%
Real Estate - Domestic - Passive	0%	0%	0%
Duration - Domestic - Passive	21%	20%	20%
Commodities - Passive	6%	6%	7%
Equities - Domestic - Div. l/s ARP	52%	53%	52%