Big Levy Investments

FINTECH A.Y. 2024/2025

POLITECNICO DI MILANO

GROUP 13

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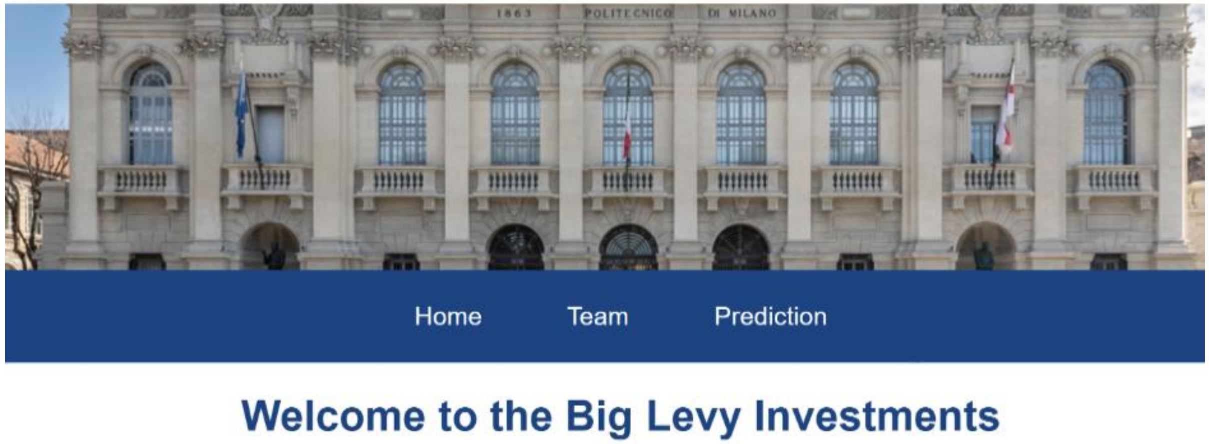
1. AIM OF THE PROJECT

This project integrates Customer Classification, Portfolio Replication and Anomaly Detection to deliver adaptive, personalized investment solutions - providing a robust tool that aligns portfolio allocations with shifting market conditions and each investor's unique objectives.

- Deliver a ready-to-use WebApp that empowers investors and advisors
- Personalized portfolio suggestions via client classification (Income vs Accumulation)
- Replica strategies that track key equity & bond benchmarks through futures-based models
- Real-time anomaly detection to shift exposure during market stress
- Cost-aware results by integrating all trading fees
- Performance monitoring for transparent, risk-adjusted evaluation



2. CUSTOMER CLASSIFICATION

Purpose & Scope

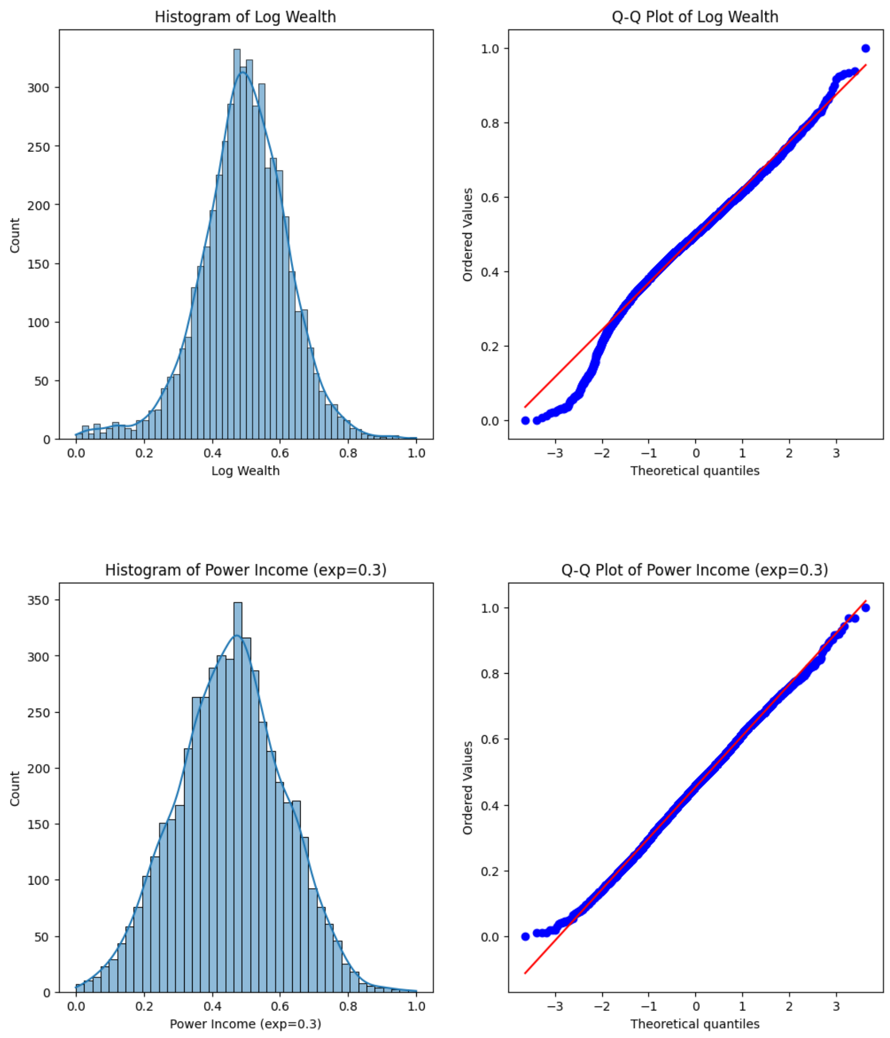
Core of the Recommender System

- Supervised-learning pipeline that predicts two client investment needs: Accumulation Investment & Income Investment.

Why it matters

- Provides fast, data-driven recommendations that plug directly into the advisory workflow.
- Built for interpretability (business users) and flexibility (future model swaps).

Variable	Description	Mean	Std	Missing	Min	Max
Age	Age, in years	55.25	11.97	0	18.00	97.00
Gender	Gender (Female = 1, Male = 0)	0.49	0.50	0	0.00	1.00
FamilyMembers	Number of components	2.51	0.76	0	1.00	5.00
FinancialEducation	Normalized level of Financial Education (estimate)	0.42	0.15	0	0.04	0.90
RiskPropensity	Normalized Risk propensity from MIFID profile	0.36	0.15	0	0.02	0.88
Income	Income (thousands of euros); estimate	62.99	44.36	0	1.54	365.32
Wealth	Wealth (thousands of euros); sum of investments and cash accounts	93.81	105.47	0	1.06	2233.23
IncomeInvestment	Boolean variable for Income investment; 1 = High propensity	0.38	0.49	0	0.00	1.00
AccumulationInvestment	Boolean variable for Accumulation/growth investment; 1 = High propensity	0.51	0.50	0	0.00	1.00



EDA

Input source: Excel workbook

- Needs (client features + labels).
- Products (product metadata).
- Metadata (variable dictionary & summaries).

Transformations

- Wealth → log(1 + x) | Income → power (0.3).
- Min-Max scale: Age, FamilyMembers, RiskPropensity, transformed Income & Wealth.

Exploratory checks

- Class balance, feature distributions, correlation heat-map, box/violin & joint plots – ensuring solid ground before modeling.

RESULTS

Modeling, Evaluation & Deliverables

Single-target & Joint-target Random-Forest models

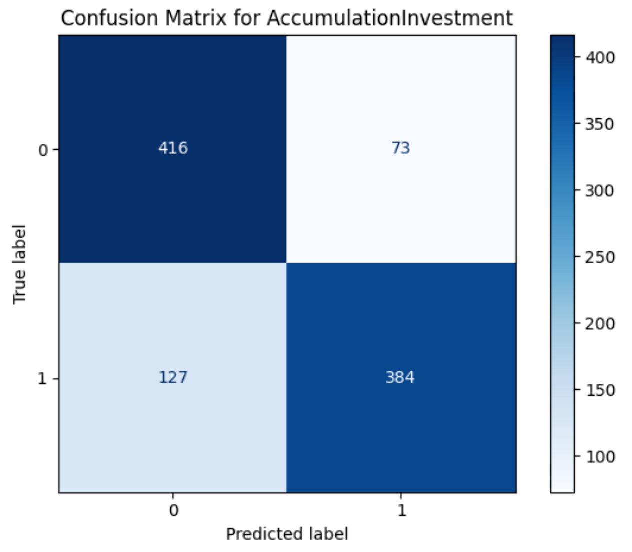
- Hyper-parameter search with Optuna
- MultiOutputClassifier for overlapping needs

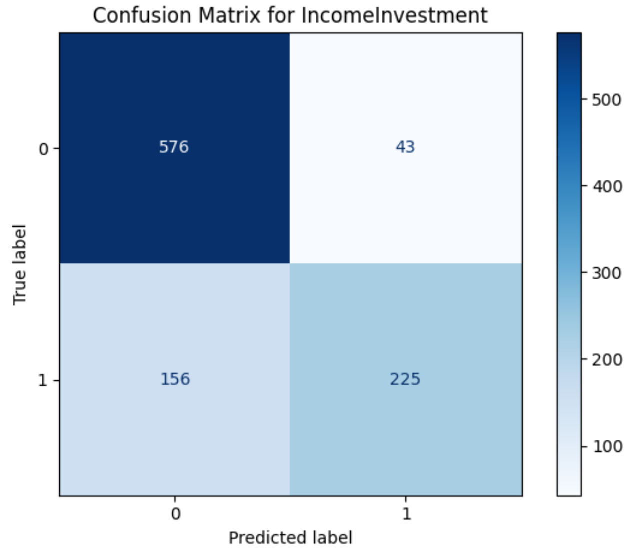
Custom evaluation

- Standard metrics + penalty score reflecting asymmetric mis-classification costs.
- Threshold (τ) tuning to maximize F1 / minimize penalty.

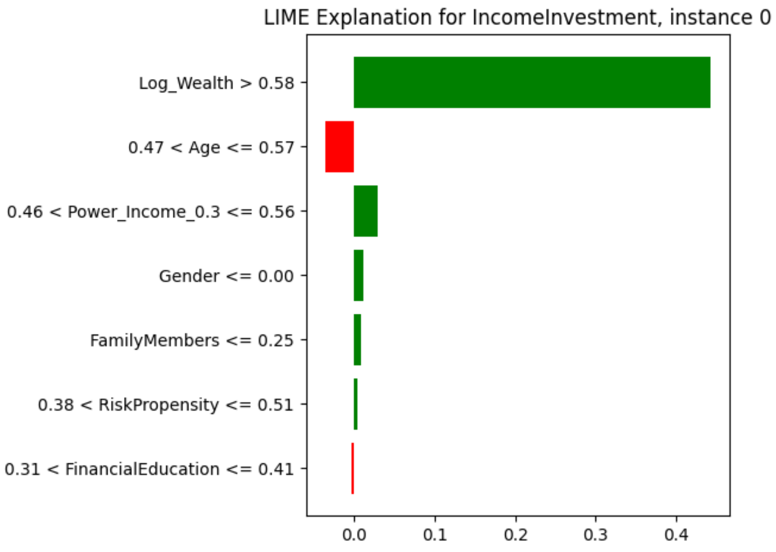
Outputs ready for production

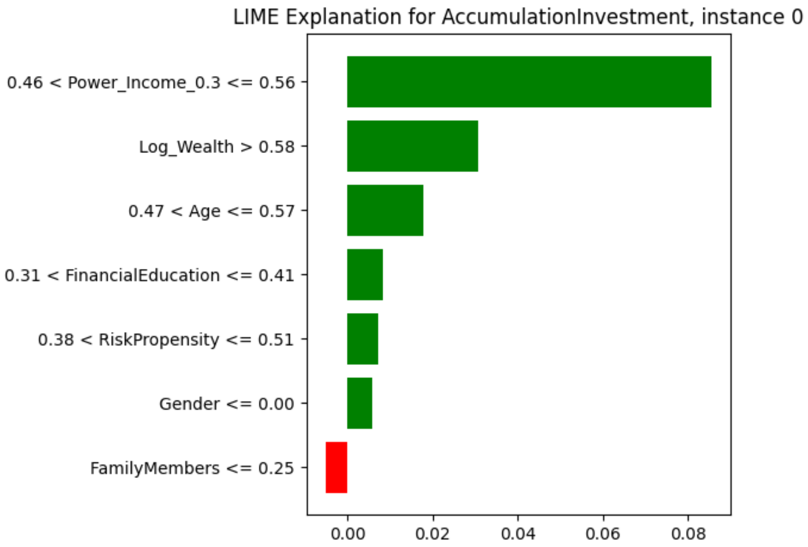
- Validation & test reports.
- Real-time methods apply full pipeline in one call – scalable, modular, and deployment-ready.





INTERPRETABILITY





- A variety of feature-importance techniques was incorporated to clarify the drivers of the model's predictions. In regulatory and production contexts, machine-learning systems must be able to explain the results they generate.

- Accordingly, local interpretability methods were added to identify the key features influencing each individual observation.

3. PORTFOLIO REPLICA

A universe of indices and futures was used, and – without insight into the target index's composition – the models were tasked with replicating its return profile.

Three reference portfolios have been replicated:

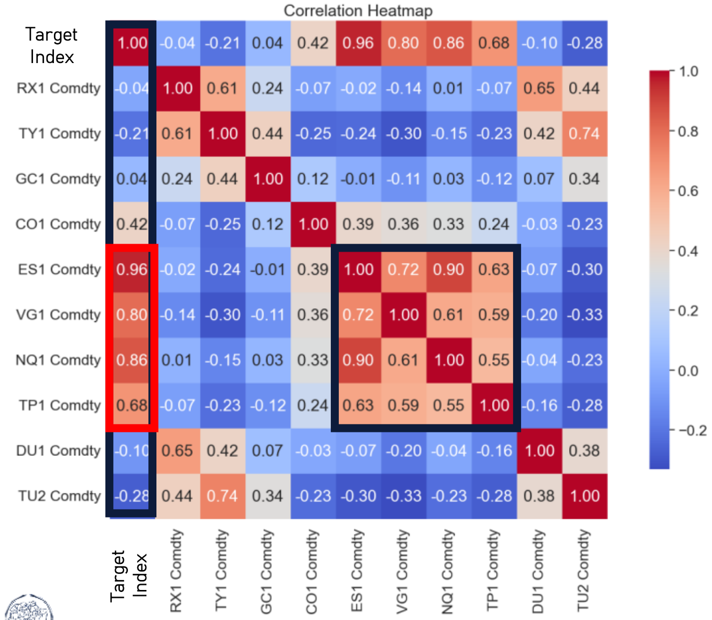
Portfolio	Index Benchmark	Essence	Risk / Return Profile
Equity*	MSCI World – MXWO	Globally diversified basket of large & mid-cap stocks	Highest growth potential; highest volatility
Bond	Bloomberg Global Aggregate – LEGATRUU	Broad investment-grade fixed-income universe	Capital preservation & steady income; lowest volatility
LifeStrategy 80/20	80 % MXWO 20 % LEGATRUU	Classic equity-bond mix for balanced exposure	Moderate growth with downside cushion

* The graphs in the Portfolio Replica section of this presentation refer to the Equity Portfolio. The results for the other portfolios can be observed in the Jupyter Notebook named *Group13_Final_Project.ipynb*.

CORRELATION ANALYSIS

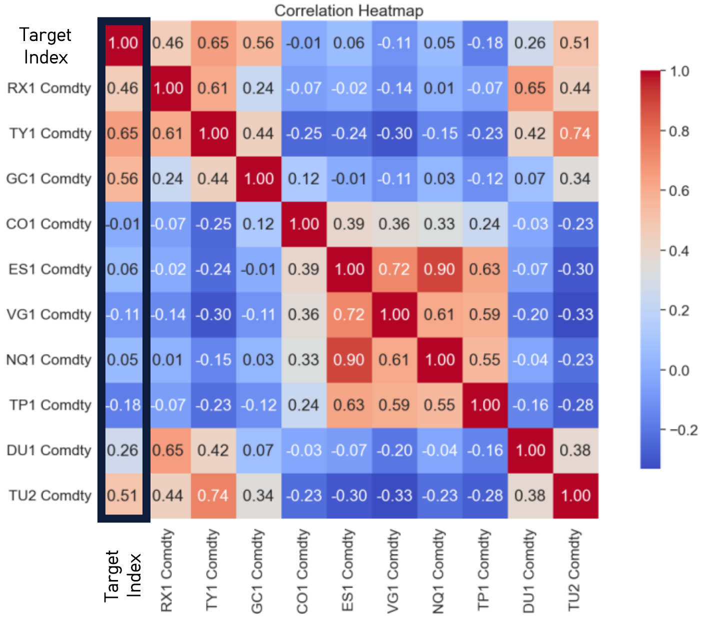
Equity Portfolio

- **Very strong anchor**: ES1 (S&P 500 mini) clocks a **ρ ≈ 0.96** with the target.
- A clear **"equity cluster"** (ES1, VG1, NQ1, TP1) all inter-correlated above **0.70**, while rate futures (RX1, TY1) are weak/negative.



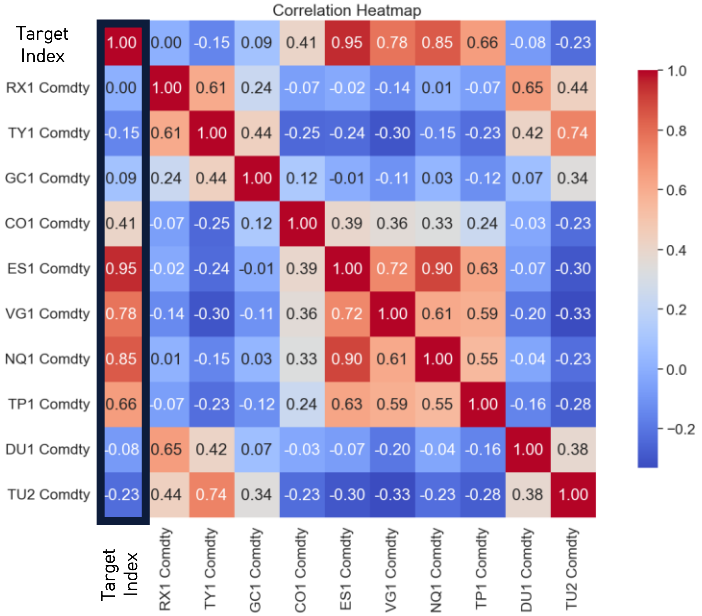
Bond Portfolio

- **Flatter matrix** – no future tops **ρ = 0.65** with the target (best is TY1, the 10-year T-Note).
- Cross-future links mostly sit in the **0.25 – 0.55** band; some pairs even drift slightly negative.



Life Strategy 80/20 Portfolio

- Hybrid profile:
  - Equity leg survives - ES1 still **ρ ≈ 0.90** with target.
  - Bond influence visible – TY1 at **ρ ≈ 0.61**.
- Matrix looks like a tempered version of the equity map.



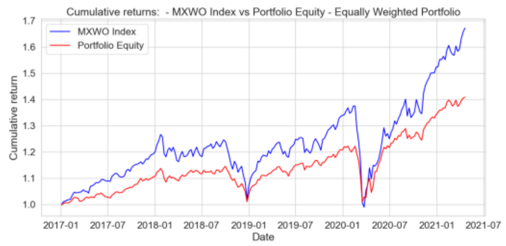
REPLICATION METHODS

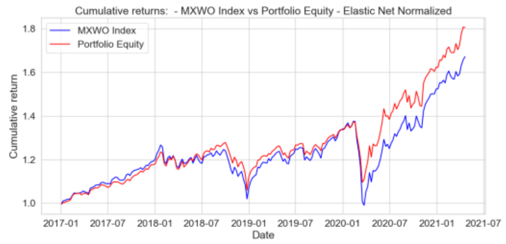
- **Equally Weighted Portfolio (EW):** benchmark method, offering simplicity and an intuitive baseline for replication.

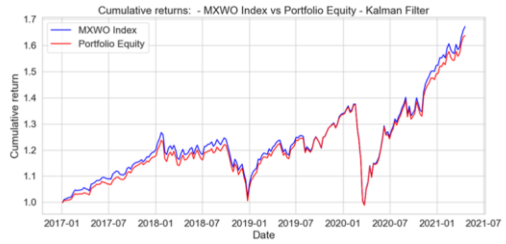
- **Elastic Net Regression (EN):** Combines L1 and L2 penalties for balanced feature selection and stable weights; might struggle with non-linear market dynamics.

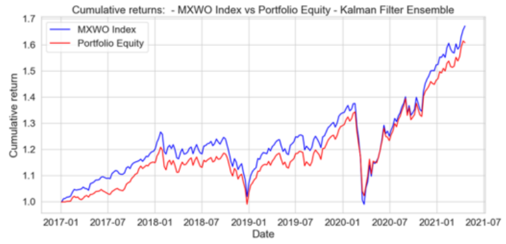
- **Kalman Filter (KF):** dynamic model that adapts weights over time, adjusting to market fluctuations. Well-suited for non-stationary data but sensitive to noise in observations. Among the considered models, KF has the shortest rebalancing window, hence it is the model with the highest costs.

- **Ensemble Kalman Filter (EKF):** The Ensemble Kalman Filter extends the classic Kalman Filter by maintaining an ensemble of possible state estimates, each updated independently to introduce flexibility and robustness to non-linearities and uncertainties. While more complex, this ensemble-based approach effectively captures the variability in optimal weights under different scenarios, producing a more adaptive and robust replication.



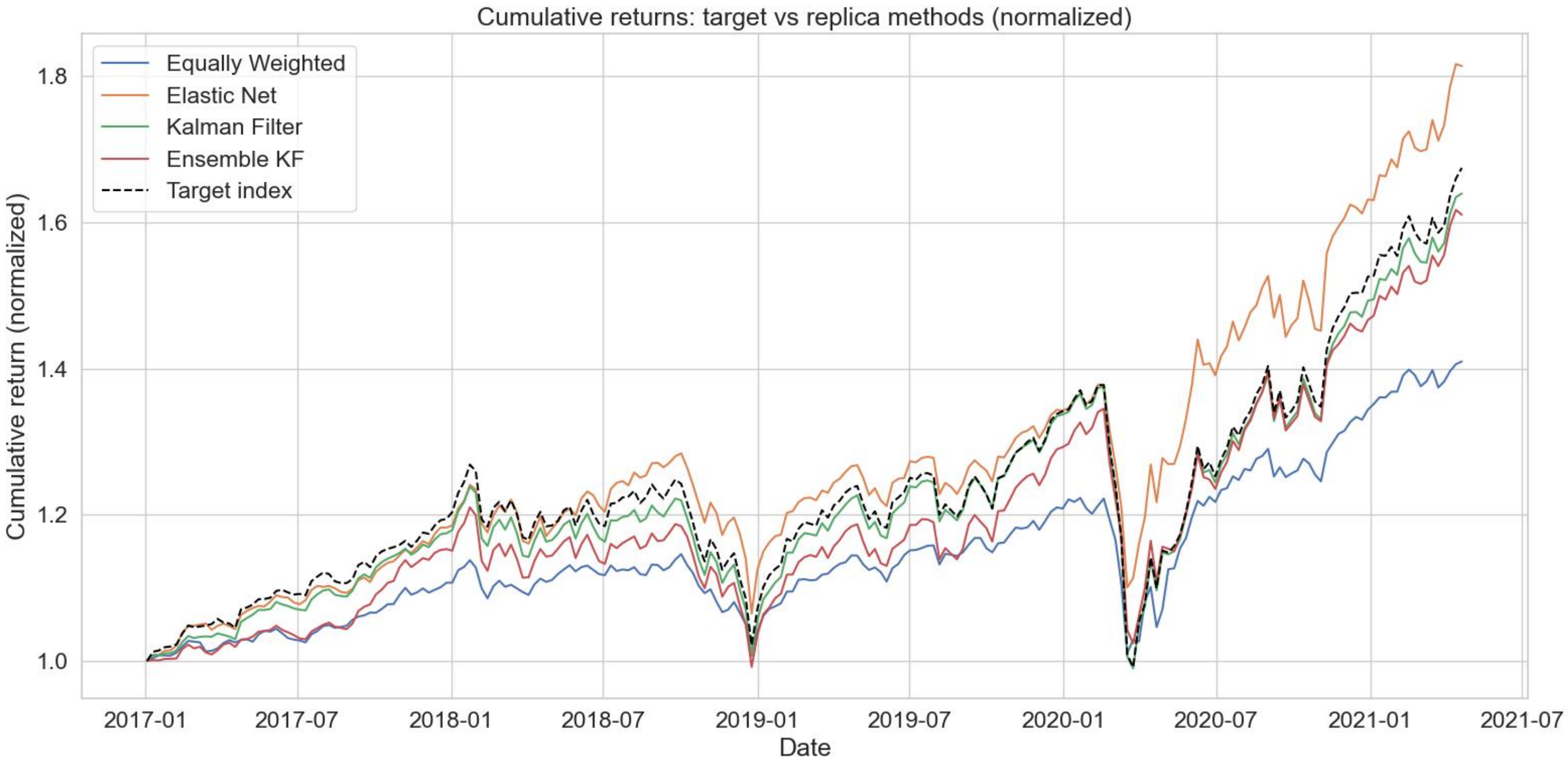






NOTE:

Comparing the replication methods, we can appreciate that the **Ensemble Kalman Filter** delivers performance nearly as strong as the Kalman Filter, while almost halving the transaction costs!

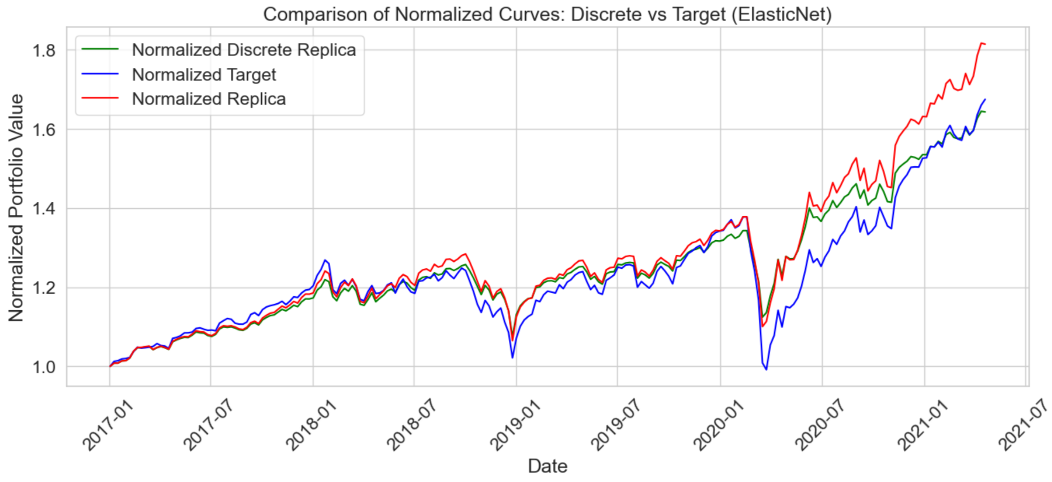


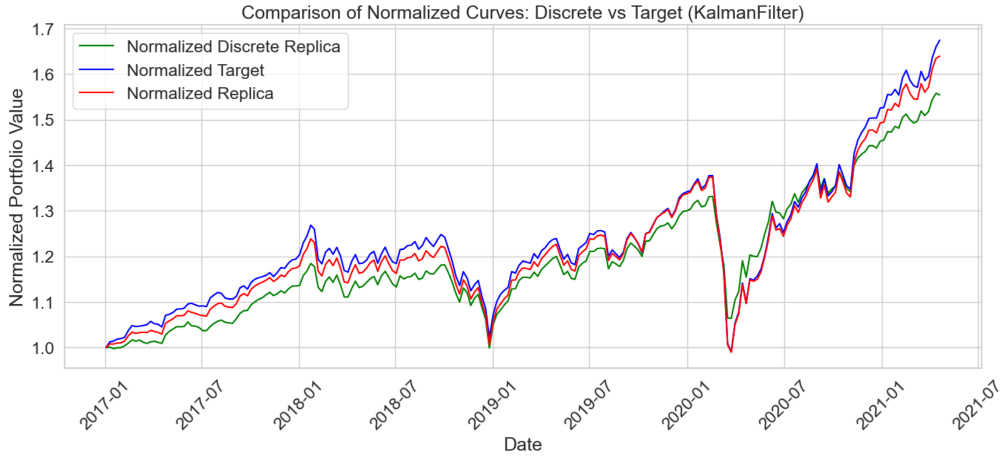
	Model	Annualized return	Annualized volatility	Sharpe ratio	Max Drawdown	Tracking Error	Information ratio	Correlation	Average gross exposure	Average VaR (1%, 1M)	Transaction cost (bp)
0	Target Portfolio	12.99%	14.66%	0.89	28.04%	N/A	N/A	N/A	N/A	N/A	NaN
1	Equally Weighted	8.38%	9.44%	0.89	17.36%	8.67%	-0.53	0.8268	1.0000	N/A	50.00
2	Elastic Net Normalized	14.55%	13.20%	1.10	20.15%	4.40%	0.35	0.9554	0.8560	7.55%	17.41
3	Kalman Filter	12.49%	14.55%	0.86	27.98%	1.15%	-0.44	0.9969	1.2735	7.36%	105.49
4	Ensemble Kalman Filter	11.92%	13.55%	0.88	23.87%	3.44%	-0.31	0.9733	1.3009	7.07%	58.85

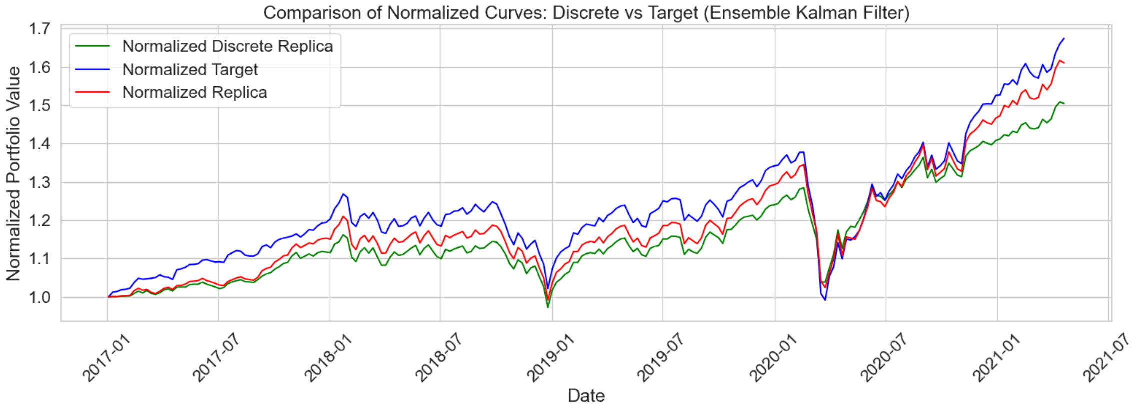
DISCRETE PORTFOLIO ALLOCATION

The analysis now shifts from continuous portfolio weights to a discrete allocation framework, in which weights are converted into actual positions for a portfolio of fixed value.

This representation more accurately mirrors the practical trading and rebalancing constraints of real markets.







4. ANOMALY DETECTION

This section analyzes anomaly detection in financial time series. Only anomalies that impacted the considered index were considered in each portfolio replica.

FINANCIAL SCORE

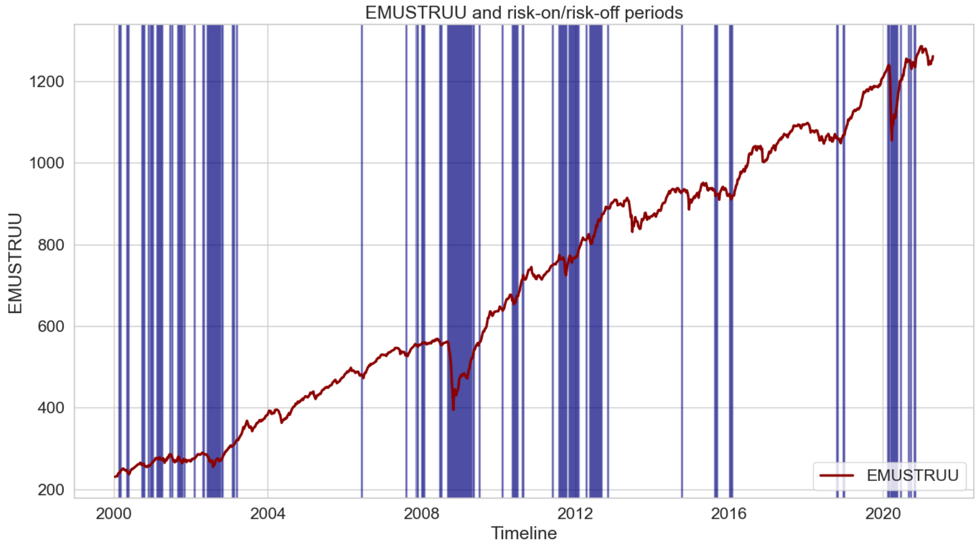
Business-oriented classification metric which measures the financial impact of classification errors based on average standardized returns for normal (*mean normal*) and anomaly (*mean anomaly*) periods, weighted by their relevance.

Cost per error:

- False Positives ($Y = 1$) incur a penalty equal to ***mean anomaly***.
- False Negatives ($Y = 0$) incur a penalty equal to ***mean normal***.
- Correct classifications carry no penalty.

- Total cost = Sum of all row-level penalties in the test set.
- Worst-case cost = Penalty that would result if every prediction were wrong.

A value of 1 denotes perfect classification, whereas 0 represents the worst possible outcome.



$$Financial\ Score = 1 - \frac{Total\ Cost}{Worst\ Case\ Cost}$$

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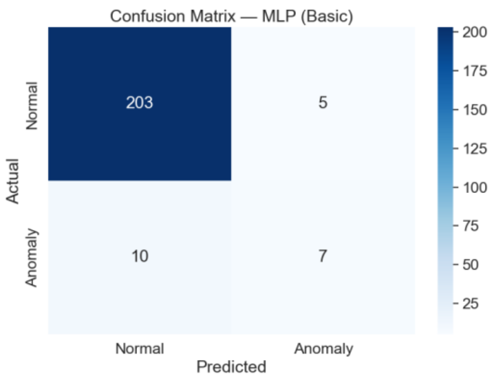
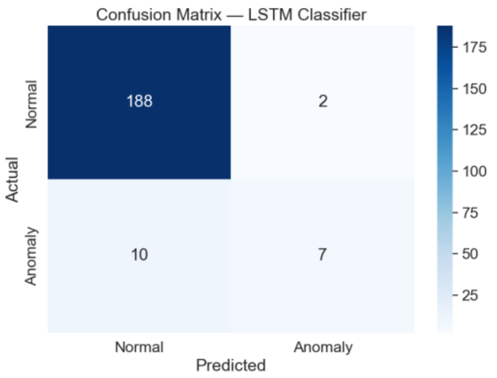
ANOMALY DETECTION MODELS

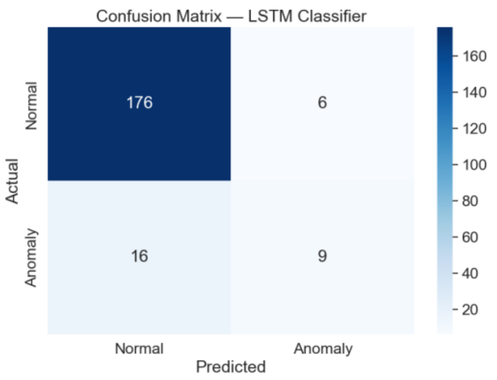
- MLP (Basic): A simple multi-layer perceptron neural network trained to classify normal vs anomaly periods.
- MLP (Optuna Tuning): The MLP model with Optuna hyperparameters tuning for better performance.
- LSTM Autoencoder: Recurrent neural network autoencoder to detect anomalies by reconstructing input sequences and identifying large reconstruction errors.
- LSTM Classifier: An LSTM-based model directly trained to classify sequences as normal or anomalous.
- LSTM Classifier with Tuned Threshold: The LSTM classifier with an adjusted classification threshold.



(a) Equity Portfolio



(b) Bond Portfolio



(c) Life Strategy 80-20 Portfolio

Confusion Matrices of the three considered portfolios best performing models.
Remind that for each model only the anomalies which had an impact on the benchmark indexes where considered.

ANOMALY DETECTION RESULTS

For each Replicating Portfolio a different Model was chosen, based on a combination of different metrics.

- Equity Portfolio: The **MLP (Basic) model** was chosen because it has the second highest Financial Score and performs as well as, or better than, the LSTM Classifier across other metrics.
- Bond Portfolio: The **LSTM Classifier** was chosen, since it outperforms the other models in almost every metric.
- Life Strategy 80-20 Portfolio: The **LSTM Classifier** was chosen since it has the highest values of Precision and F1 score and it has the second highest Financial Score.

Model	# Anomalies Detected	Precision	Recall	F1 Score	Financial Score
MLP (Basic)	12	0.5833	0.4118	0.4828	0.8877
MLP (Optuna Tuning)	24	0.3750	0.5294	0.4390	0.7893
LSTM Autoencoder	29	0.3103	0.5294	0.3913	0.7481
LSTM Classifier	10	0.6000	0.3529	0.4444	0.8948
LSTM Classifier with Tuned Threshold	11	0.5455	0.3529	0.4286	0.8856

(a) Equity Portfolio

Model	# Anomalies Detected	Precision	Recall	F1 Score	Financial Score
MLP (Basic)	38	0.2632	0.4762	0.3390	0.6389
MLP (Optuna Tuning)	0	0.0000	0.0000	0.0000	0.7150
LSTM Autoencoder	32	0.4062	0.6190	0.4906	0.7173
LSTM Classifier	9	0.7778	0.3333	0.4667	0.7485
LSTM Classifier with Tuned Threshold	13	0.5385	0.3333	0.4118	0.7240

(b) Bond Portfolio

Model	# Anomalies Detected	Precision	Recall	F1 Score	Financial Score
MLP (Basic)	16	0.6250	0.4000	0.4878	0.7544
MLP (Optuna Tuning)	73	0.2603	0.7600	0.3878	0.5092
LSTM Autoencoder	30	0.4333	0.5200	0.4727	0.7039
LSTM Classifier	14	0.7143	0.4000	0.5128	0.7514
LSTM Classifier with Tuned Threshold	19	0.5789	0.4400	0.5000	0.7310

(c) Life Strategy 80-20 Portfolio

5. REPLICA WITH ANOMALY DETECTION

We combined the portfolio replication strategies with the anomaly detection signals.

Whenever an anomaly was detected, we dynamically shifted the allocation to cash by setting the portfolio weights to zero, testing how this approach influenced overall performance and risk.

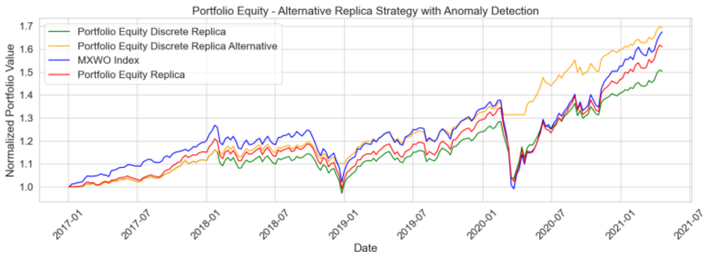
Two overlay methods were considered.

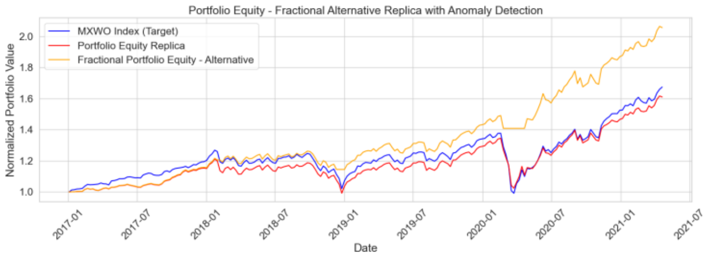
Overlay	Weights	Advantage	Drawback
Discrete	Rounded positions for a fixed-value book.	Real- world tradability	Extra noise & costs
Fractional	Original fractional weights from the replication model.	Higher risk-adjusted returns; keeps model precision	Requires fractional execution capability

Key Findings:

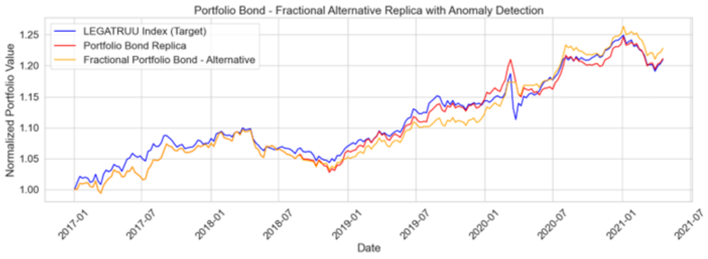
- Continuous-weight overlay preserves model precision and delivers the best risk-adjusted results.
- Discrete overlay is more realistic but introduces extra implementation noise and transaction costs.

(a) Equity Portfolio

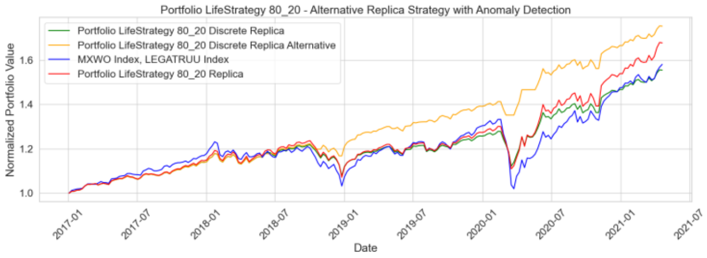


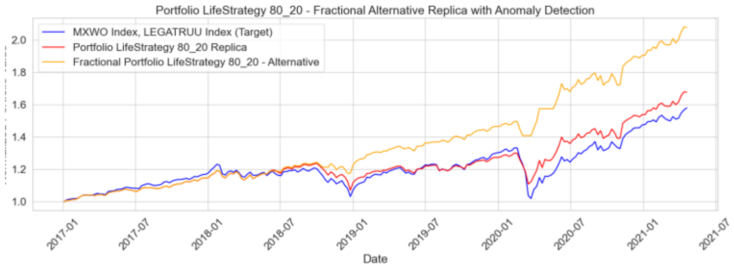


(b) Bond Portfolio



(c) Life Strategy 80-20 Portfolio





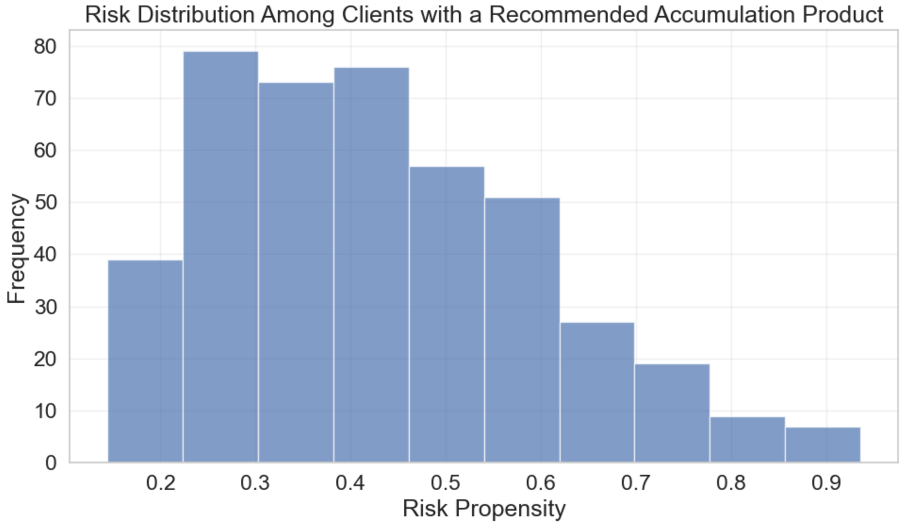
6. RECOMMENDER SYSTEM (NBA ALGORITHM)

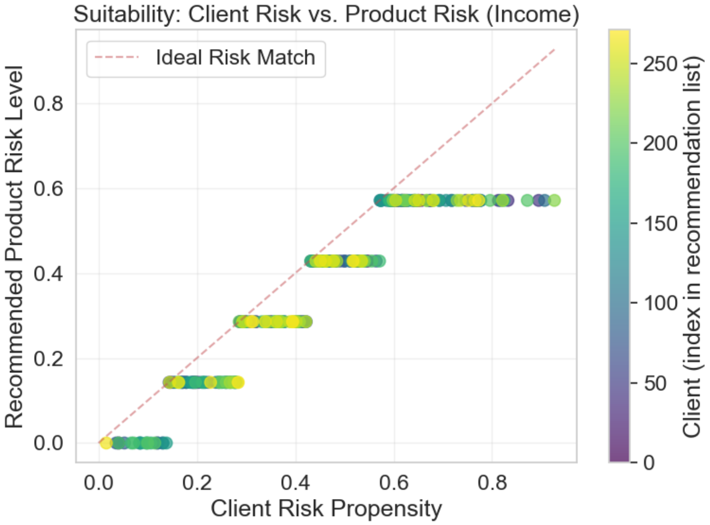
- The classified customer profiles were linked to the portfolio options to create a personalized investment recommender.
- Given a new customer's segment, the system suggests one of the six portfolios (or a blend), aiming to match the investor's risk-return needs. The recommender was tested on a hold-out set, measuring how often its recommendations align with a reference (simulated) "optimal" choice.
- Evidence in the test set show that our model can generalize beyond the training sample. In practice, this means the approach could realistically support portfolio selection in a wealth-management context, offering personalized allocations that resonate with each investor's profile.

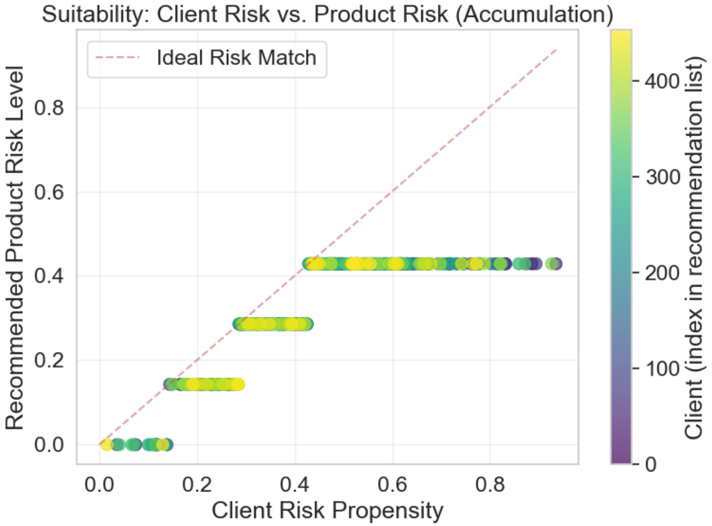
#	Client ID	Product	Risk Propensity	Product Risk
1	1055	ETF_equity	**0.8866**	0.4286
2	705	ETF_equity	0.5467	0.4286
3	2413	ETF_life	0.3230	0.2857

#	Client ID	Product	Risk Propensity	Product Risk
1	1501	ETF_equity	0.4566	0.4286
2	705	ETF_equity	0.5467	0.4286
3	589	ETF_equity	0.4522	0.4286


Risk Distribution Among Clients with a Recommended Income Product
Frequency
Risk Propensity


Risk Distribution Among Clients with a Recommended Accumulation Product
Frequency
Risk Propensity


Suitability: Client Risk vs. Product Risk (Income)
Ideal Risk Match
Recommended Product Risk Level
Client Risk Propensity
Client (index in recommendation list)


Suitability: Client Risk vs. Product Risk (Accumulation)
Ideal Risk Match
Recommended Product Risk Level
Client Risk Propensity
Client (index in recommendation list)

7. VISIT OUR WEB APP

To tie our work together we decided to develop a WebApp which gives a great idea of real-world applications and possible development of our work.

Find it at:
https://gm46.pythonanywhere.com/