Scenario-Based Machine Learning for Portfolio Optimization

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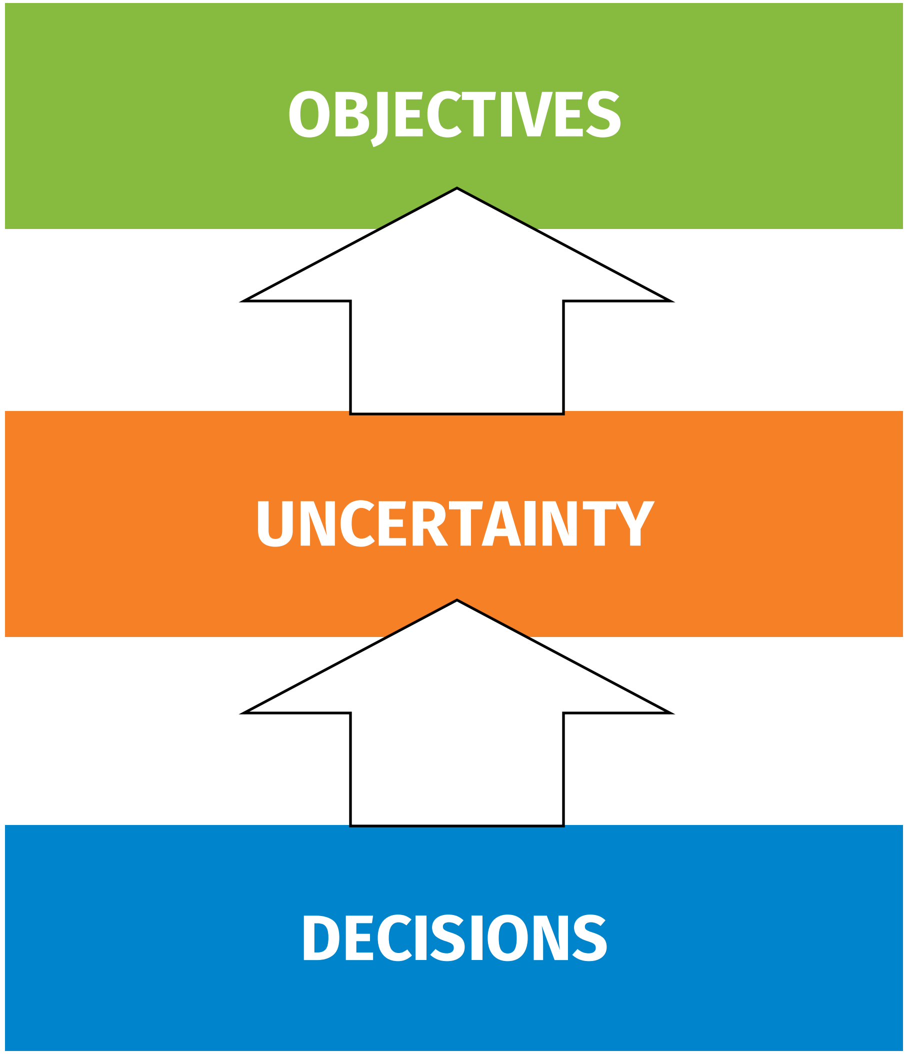
Investment decision problem



Risk – return – horizon – inflation – cash flows – liquidity – liabilities – solvency – ESG – ...

Financial – economic – monetary policy – Philips curve – demographics – r^* / low rates – COVID-19 – climate – ...

Asset allocation – rebalancing – matching – overlays – options – factors – ESG – ...

Portfolio optimization problem

- Given a portfolio that consists of K number of assets, how can we find the most optimal combination of asset weights $\boldsymbol{w} = (w_1, w_2, \dots, w_K)$ in the feasible region $\boldsymbol{W}$?

- Maximize a measure of return $f_{return}(\boldsymbol{w})$ while minimizing a measure of risk $f_{risk}(\boldsymbol{w})$

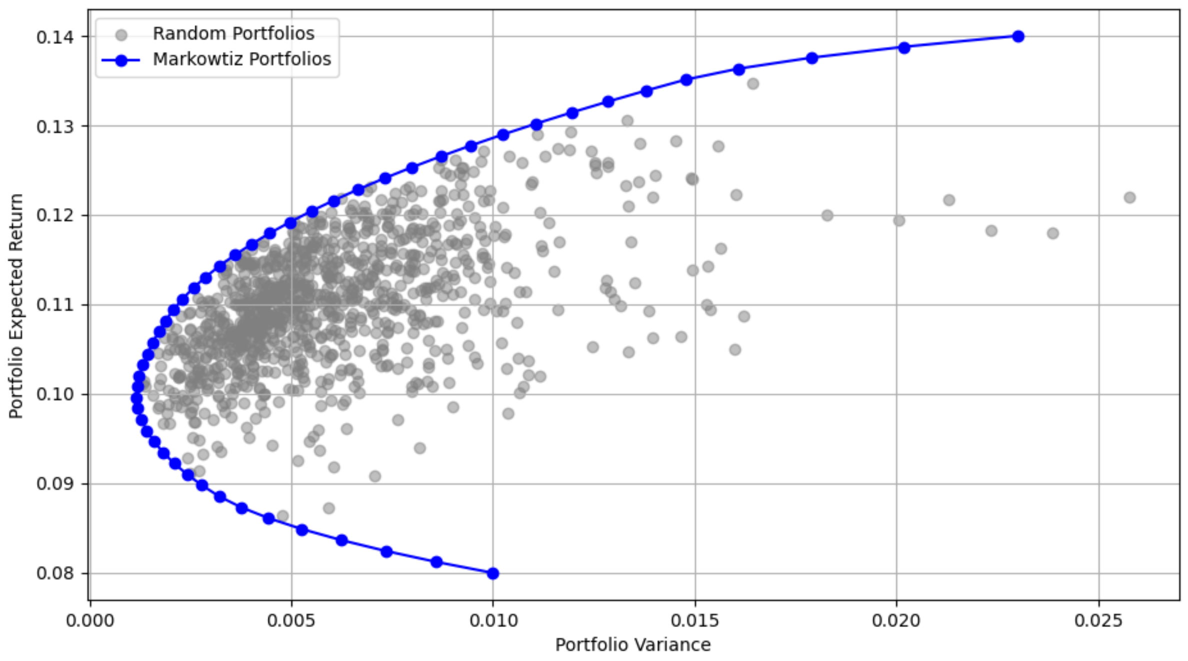
- Subject to constraints on asset weights (the feasible region $\boldsymbol{W}$)

Mean Variance Optimization

Minimize the variance (risk) and maximize the expectation of portfolio return (return)

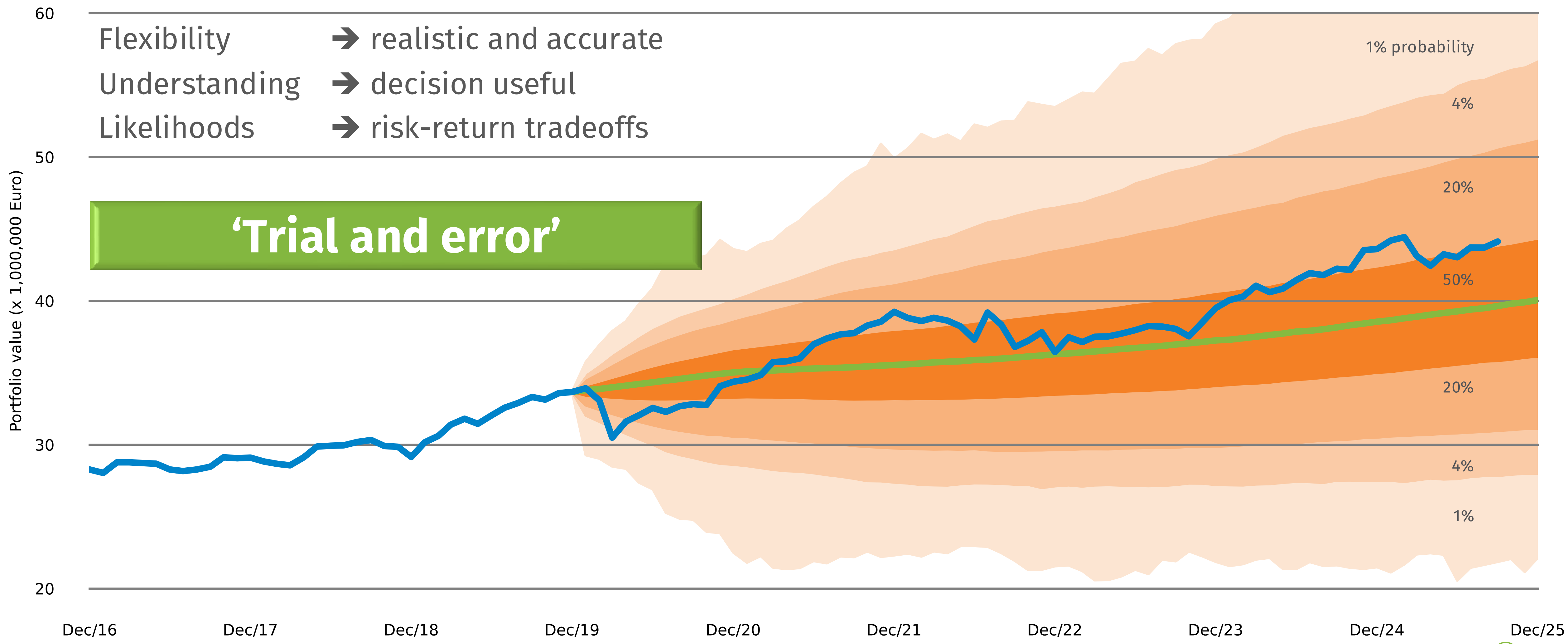
- Minimize variance of portfolio return: $\sigma_p = w^T \Sigma w$
- Subject to constraints:
  - Expected portfolio return $w^T \mathbb{E}[R_t]$ = target return
  - Sum of portfolio weights w = 100%
  - Other linear constraints on portfolio weights
- Where:
  - w = vector of portfolio weights
  - $\mathbb{E}[R_t]$ = vector of expected returns
  - Σ covariance matrix of returns

Closed form solution



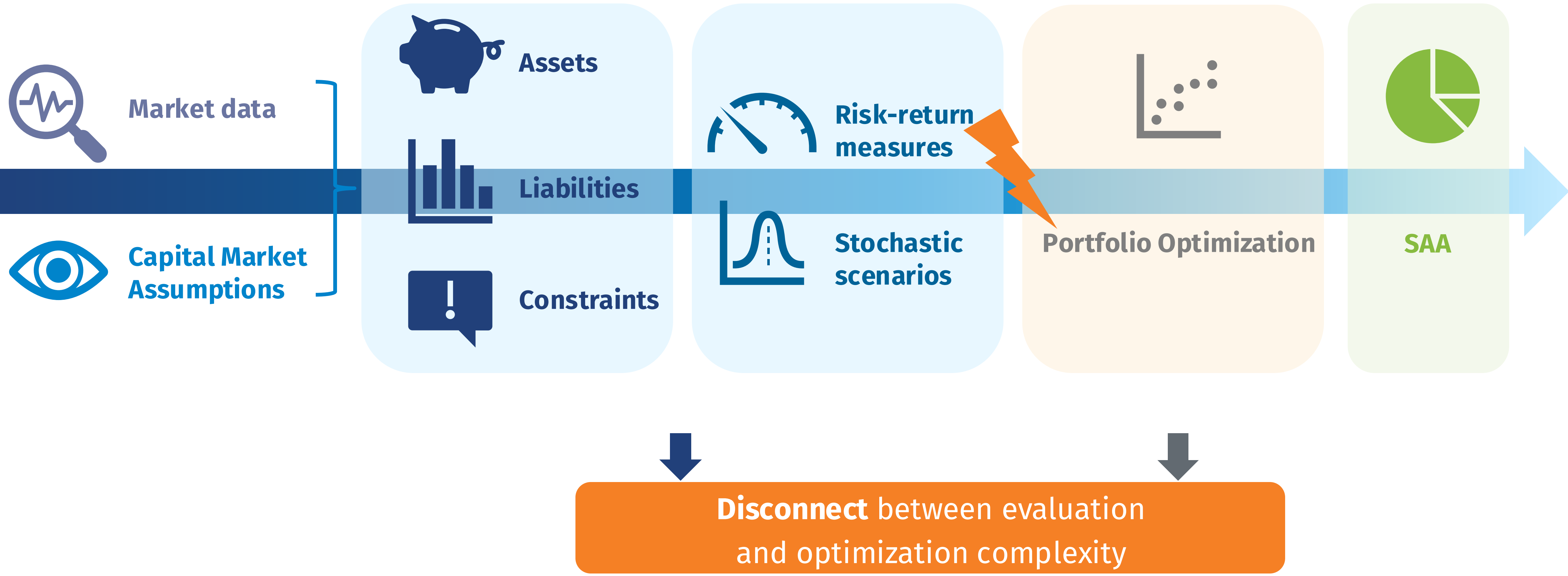
Stochastic scenario approach

Evaluate portfolio performance on ‘any’ set of investor specific risk and return measures



Portfolio of 15 million Euro at the end of 2005 simulated forward on a monthly basis assuming an investment strategy with an asset allocation of 50% fixed income (60% government bonds, 40% corporate bonds), 25% global equities and 25% alternatives (including real estate), bi-annual rebalancing and a quarterly 50% hedge of all FX risk. The blue line represents the realized value of the portfolio until the end of September 2025. The orange “fan chart” represents the possible scenario developments of the value of the portfolio based on the December 2019 Ortec Finance scenario outlook in terms of the 1%, 5%, 25%, 75%, 95% and 99% percentiles.

Strategic Asset Allocation framework



Long-standing problem

ELSEVIER

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Theory and Methodology

A hybrid simulation/optimisation scenario model for asset/liability management

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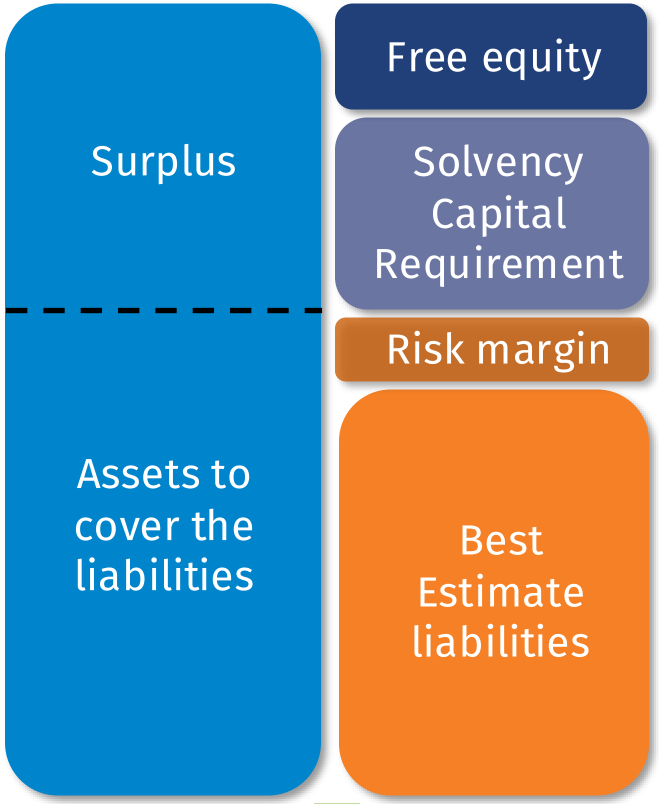
1. The applied scenario analysis approach.
2. The application of simulation *and* optimisation models.
3. The application of a hybrid simulation/optimisation model which enables the optimisation of the asset allocation, consistently taking into account all the functionalities of the simulation model.
4. The attitude of being a consultant rather than only a technical model builder. That is, the models are adjusted to the situation and understanding of the client, rather than vice versa – and the level of ambition is to use model building to improve the information and understanding of the clients, rather than just confronting management with 'optimal' solutions.

In practice it turns out that the asset/liability decision making process is greatly improved by considering efficient frontiers of initial asset allocations which, given certain values of the average contribution rates minimise the value of any specified risk measure (by the initial asset allocation we refer to the allocation which is hold in the first year of each scenario, and which, unless a rebalancing strategy is followed, may be adjusted according to the preset decision rules in the years thereafter). Due to the many complex interdependencies involved, it is evident that a man-driven search to these initial optimal asset allocations would require a prohibitive time period (if it would ever converge to optimality at all).

Example: Insurance PVDE optimization

PVDE = ‘Present Value of Distributable Earnings’

- Life insurer under Risk-Based Capital framework
- If Solvency Ratio (SR) is high, dividends are paid
- If SR is low, capital injections are called for
- Optimization problem:
  - Objective: Maximize PVDE and minimize capital injections on 10-year horizon
  - Decisions: SAA portfolio weights
  - Constraints: sum portfolio weights 100% and min/max portfolio weights

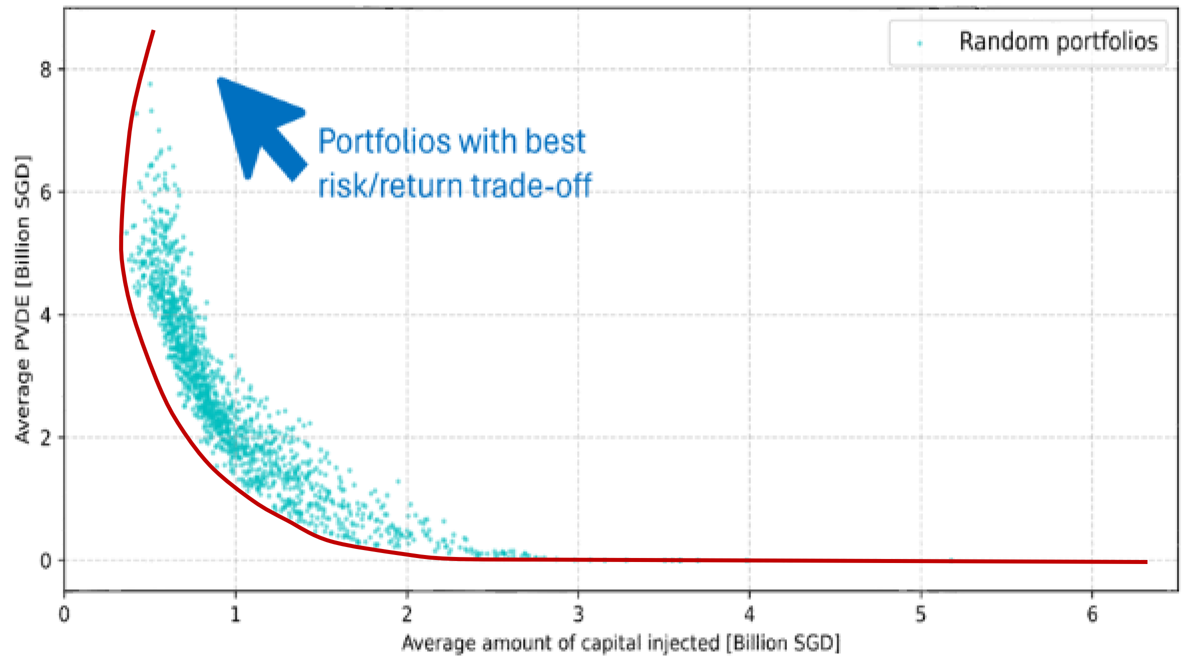


$$Solvency\ Ratio = \frac{Surplus}{SCR}$$

Approach 1: pure trial-and-error

Accurate, but:

- Slow man-driven search
- Heavy computational burden
- No guarantee of optimality



Case details

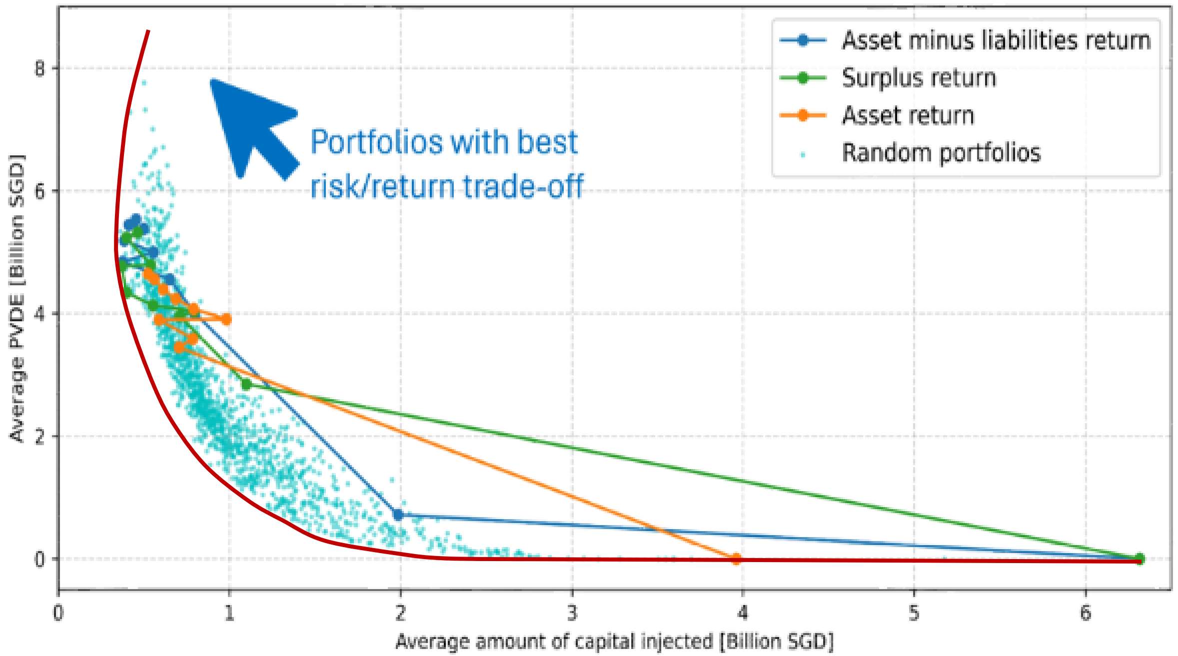
- 2000 economic scenarios with 10 asset classes
- Annual rebalancing to the optimized static portfolio weights within a time horizon of 10 years

Approach 2: Markowitz and hope for the best

Or other closed-form optimizers

Fast, but:

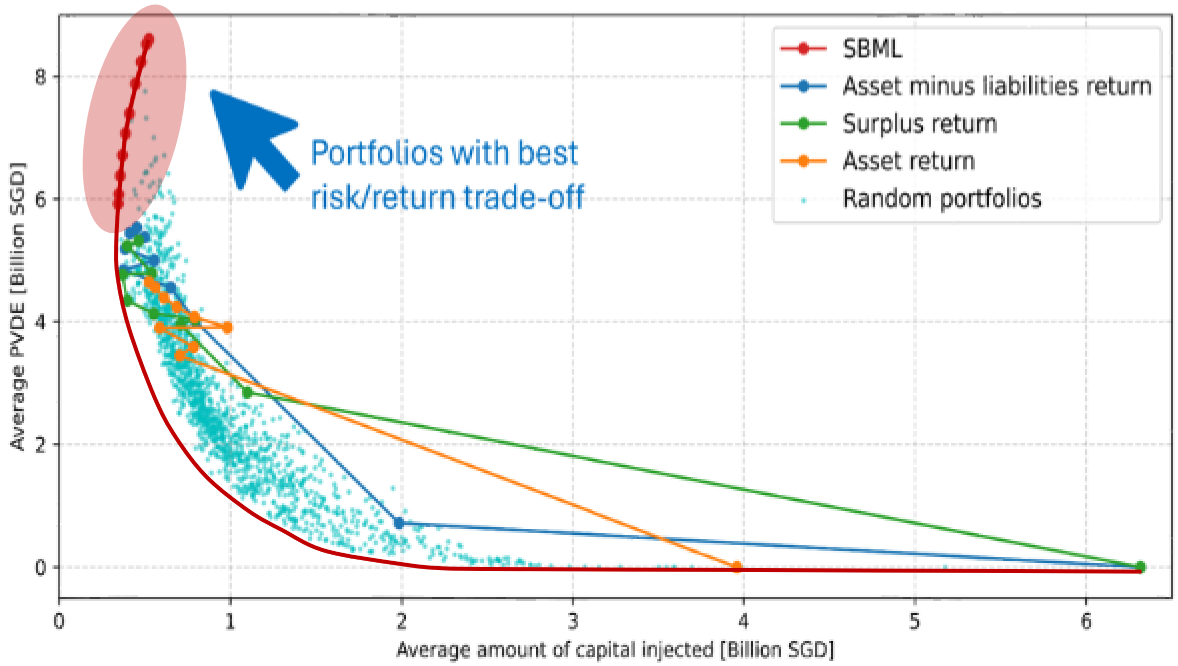
- Only perform well for relatively simple and unrealistic risk-return objectives (and not for PVDE)
- Case by case solutions (if any)



Scenario-Based Machine Learning – What it can do

The best of both worlds – realistic and “easy” to find optimal portfolios

- Combines the flexibility and accuracy of a stochastic scenario approach with the efficiency of closed-form optimizers
- By training Machine Learning algorithms on infinite training data from stochastic scenarios
- Generic approach to optimize on any combination of risk-return measures that can be evaluated in a stochastic scenario approach



Scenario-Based Machine Learning – How it works

Three-step approach

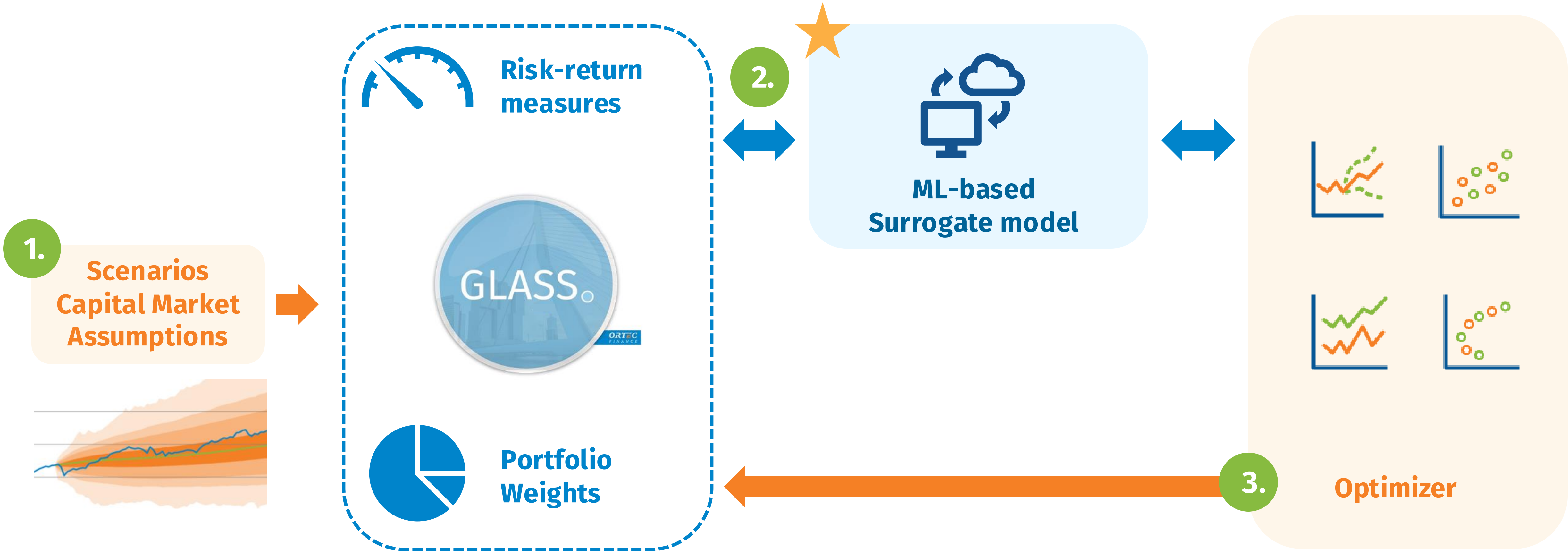
1. **Initialization**: Generate scenarios based on Capital Market Assumptions to evaluate portfolios on in terms of investor specific risk-return measures

2. **Calibration**: Simulate various (random) portfolios and estimate (ML-based) surrogate models

3. **Optimization**: Find portfolios that perform best on the investor specific risk-return measures in surrogate space and evaluate in full scenario model

Scenario-Based Machine Learning – How it works

Three-step approach



Surrogate model design and calibration are key (step 2)

- Given a simulation environment for a set of scenarios S, we assume that the risk-return measures that we are interested in, $(f_1(\boldsymbol{w}\,|S), f_2(\boldsymbol{w}\,|S), \dots)$, are expensive to evaluate

- Solution: estimate a surrogate model $\tilde{f}(\boldsymbol{w}|S)$ for each objective and find the "pareto set" of portfolio weights in surrogate space:

$$\min_{\boldsymbol{w}\in\boldsymbol{W}} \hat{\boldsymbol{f}}(\boldsymbol{w}|S), \qquad \text{where } \hat{\boldsymbol{f}}(\boldsymbol{w}|S) = (\hat{f}_1(\boldsymbol{w}|S), \hat{f}_2(\boldsymbol{w}|S), \dots)$$

- The surrogate models function as a proxy for the expensive evaluations and allow us to quickly evaluate possible solutions

- Choice of (ML-) model family is flexible, as long as the surrogate model can be evaluated fast

Optimizing over the surrogate models is “easy” (step 3)

- When we want to optimize, we need a single “reward” that represents how good a portfolio is in line with the investor specific risk-return measures

- Transform the multi-objective problem to a single objective one with linear scalarization:

$$\max_{\boldsymbol{w} \in \boldsymbol{W}} \hat{f}(\boldsymbol{w}), \qquad \text{where } \hat{f}(\boldsymbol{w}) = (1 - \alpha)\hat{f}_{return}(\boldsymbol{w}) - \alpha \hat{f}_{risk}(\boldsymbol{w}),$$
$$\alpha \in [0, 1]$$

- Solve this optimization problem over a (uniform) grid of values for α with fast numerical solvers

- This specification also allows for adding other components depending on $\boldsymbol{w}$ into the objective function, e.g. a diversification penalty

And can be extended to high dimensional optimization

- The speed of the optimization step allows us to also optimize in higher dimensional spaces

$$\max_{\boldsymbol{w} \in \boldsymbol{W}} \hat{\boldsymbol{f}}(\boldsymbol{w}), \qquad \text{where } \hat{\boldsymbol{f}}(\boldsymbol{w}) = (1 - \alpha_1 - \alpha_2)\hat{f}_{return}(\boldsymbol{w}) - \alpha_1 \hat{f}_{risk,1}(\boldsymbol{w}) - \alpha_2 \hat{f}_{risk,2}(\boldsymbol{w})$$

$$\alpha_1 + \alpha_2 \leq 1$$

$$\alpha_1, \alpha_2 \in [0, 1]$$

- Makes it possible to find an optimal "plane" of portfolios for a tradeoff between multiple risk and return measures

- Difficulty is <u>not</u> in the actual optimization, but in the human interpretation

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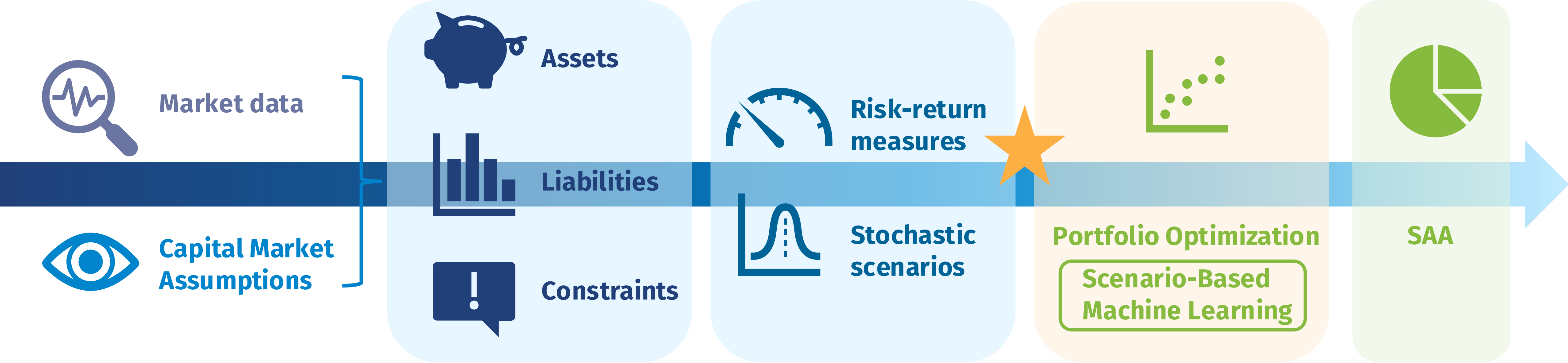
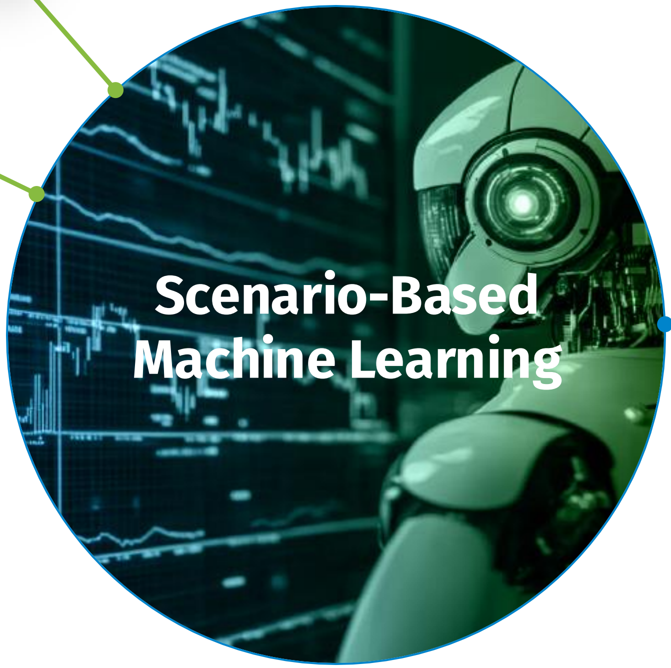
Loop completed!

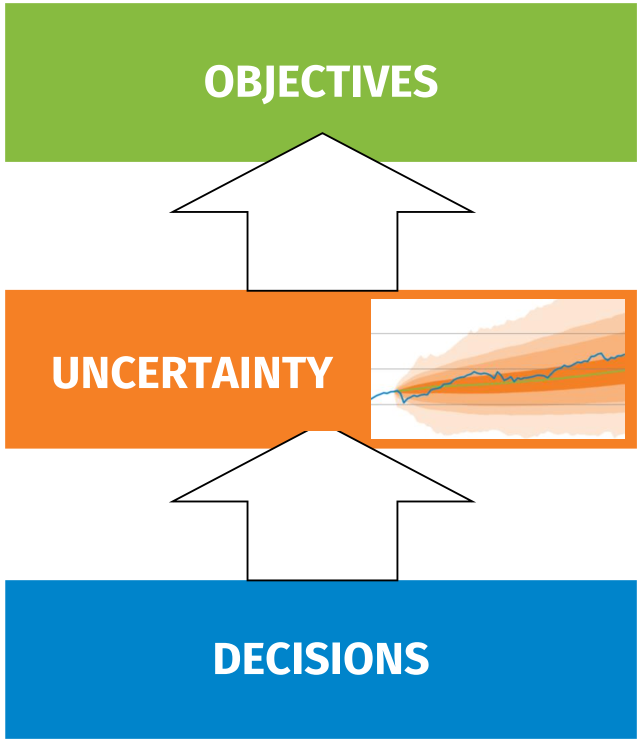


Solvency Capital Requirements

Present Value of Distributable Earnings

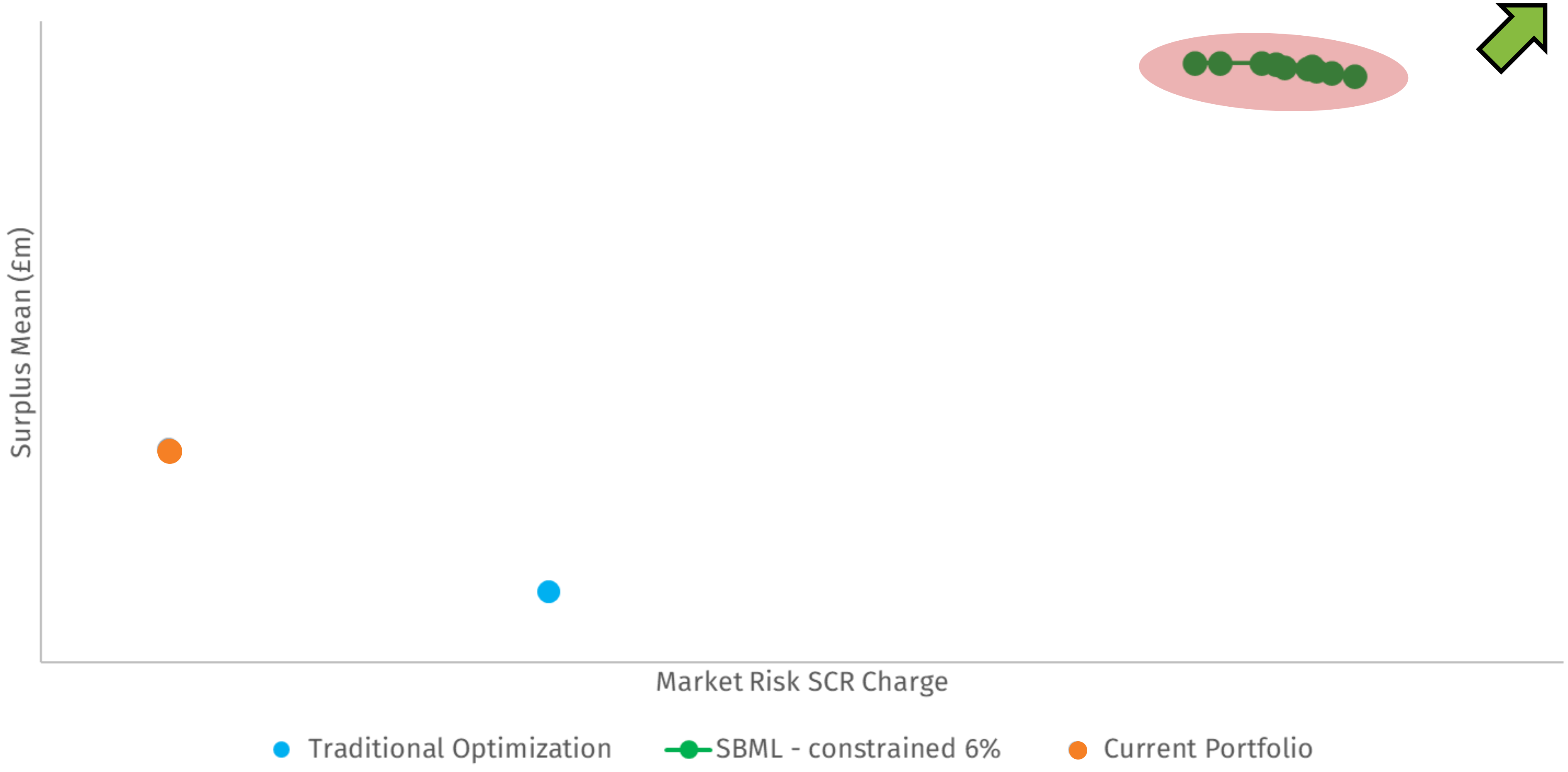


SAA



Solvency Capital Requirements

Constrain Market Risk SCR Charge between 5%-6%



Pension
Funded Ratio

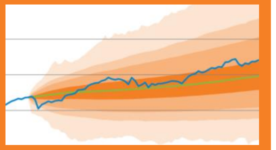
Solvency Capital
Requirements

Present Value of
Distributable Earnings

SAA

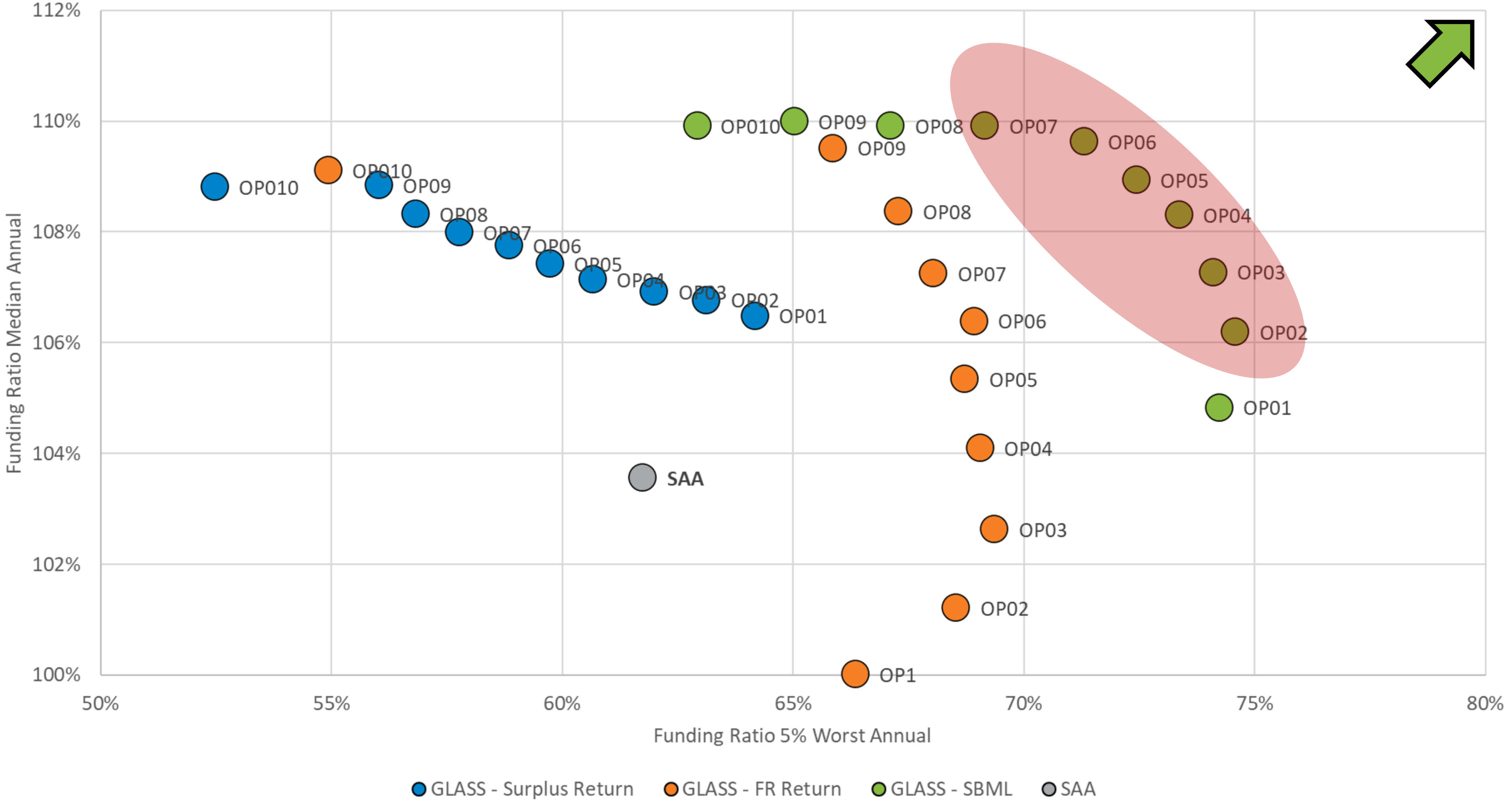
OBJECTIVES

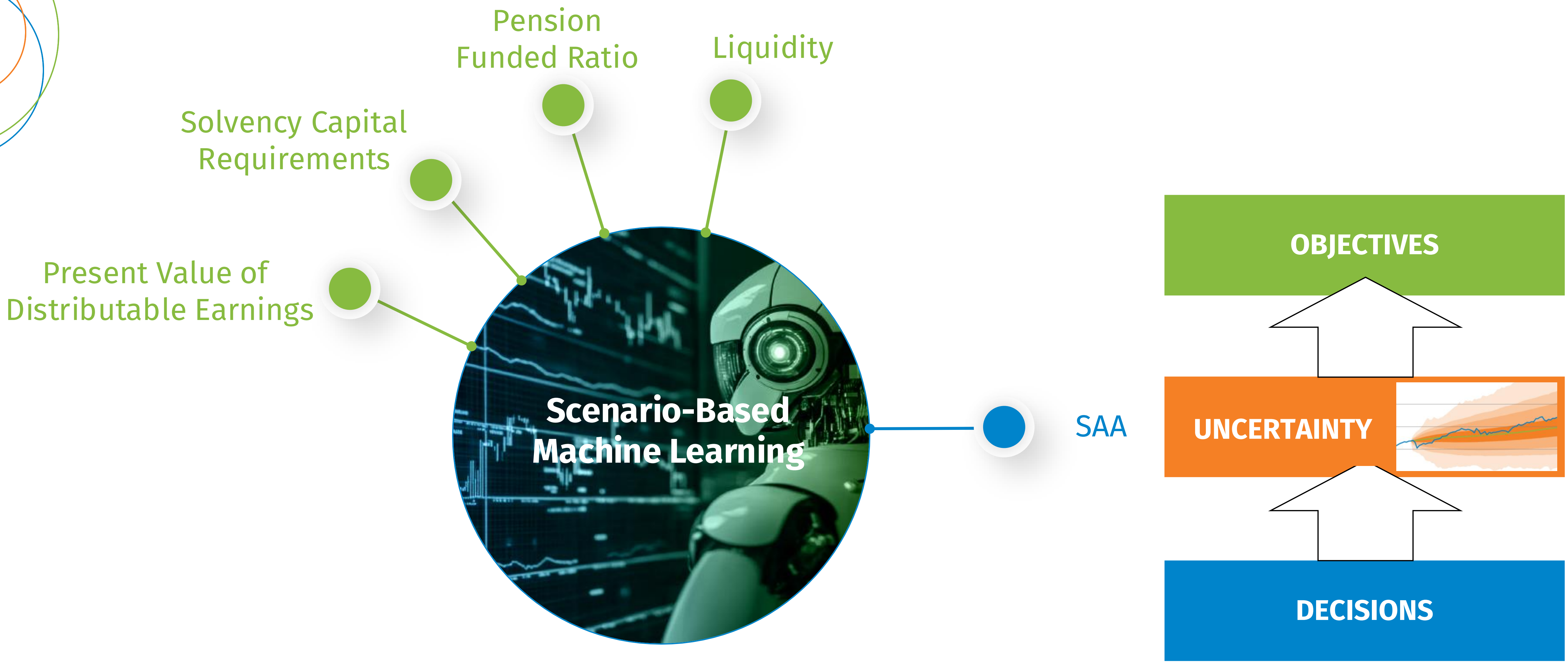
UNCERTAINTY



DECISIONS

Pension Funded Ratio

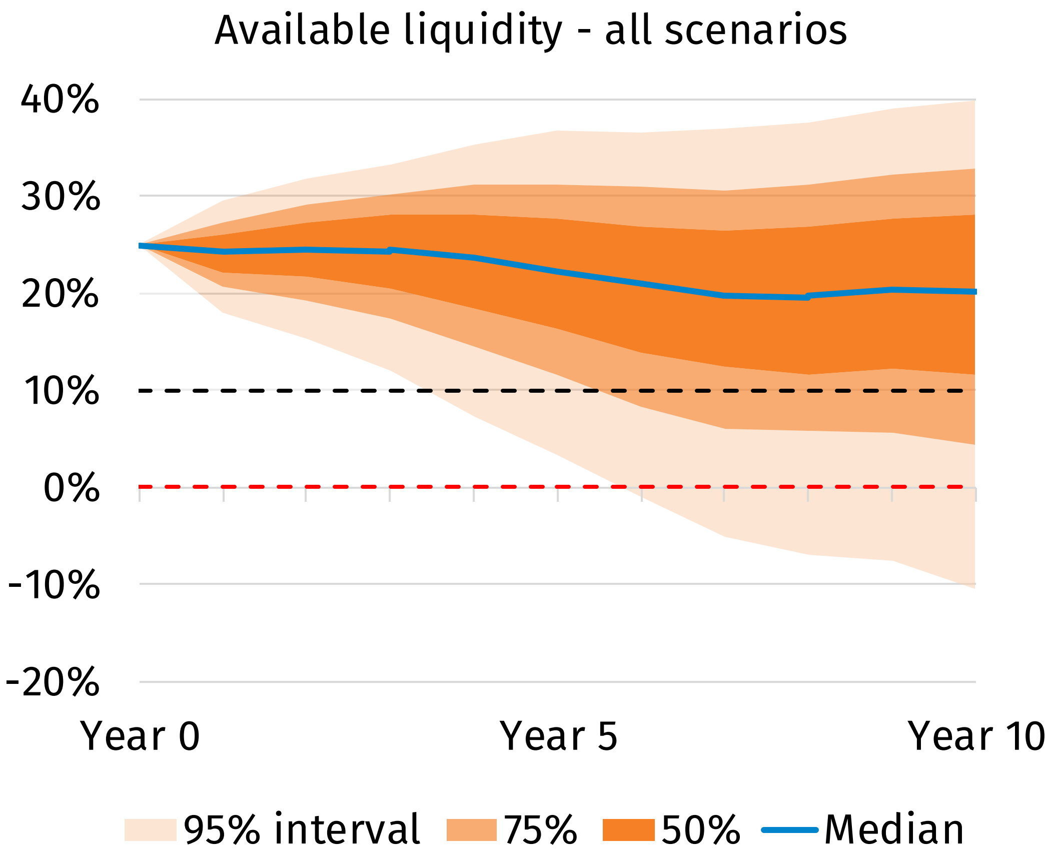



Pension
Funded Ratio
Liquidity
Solvency Capital
Requirements
Present Value of
Distributable Earnings
Scenario-Based
Machine Learning
SAA
OBJECTIVES
UNCERTAINTY
DECISIONS

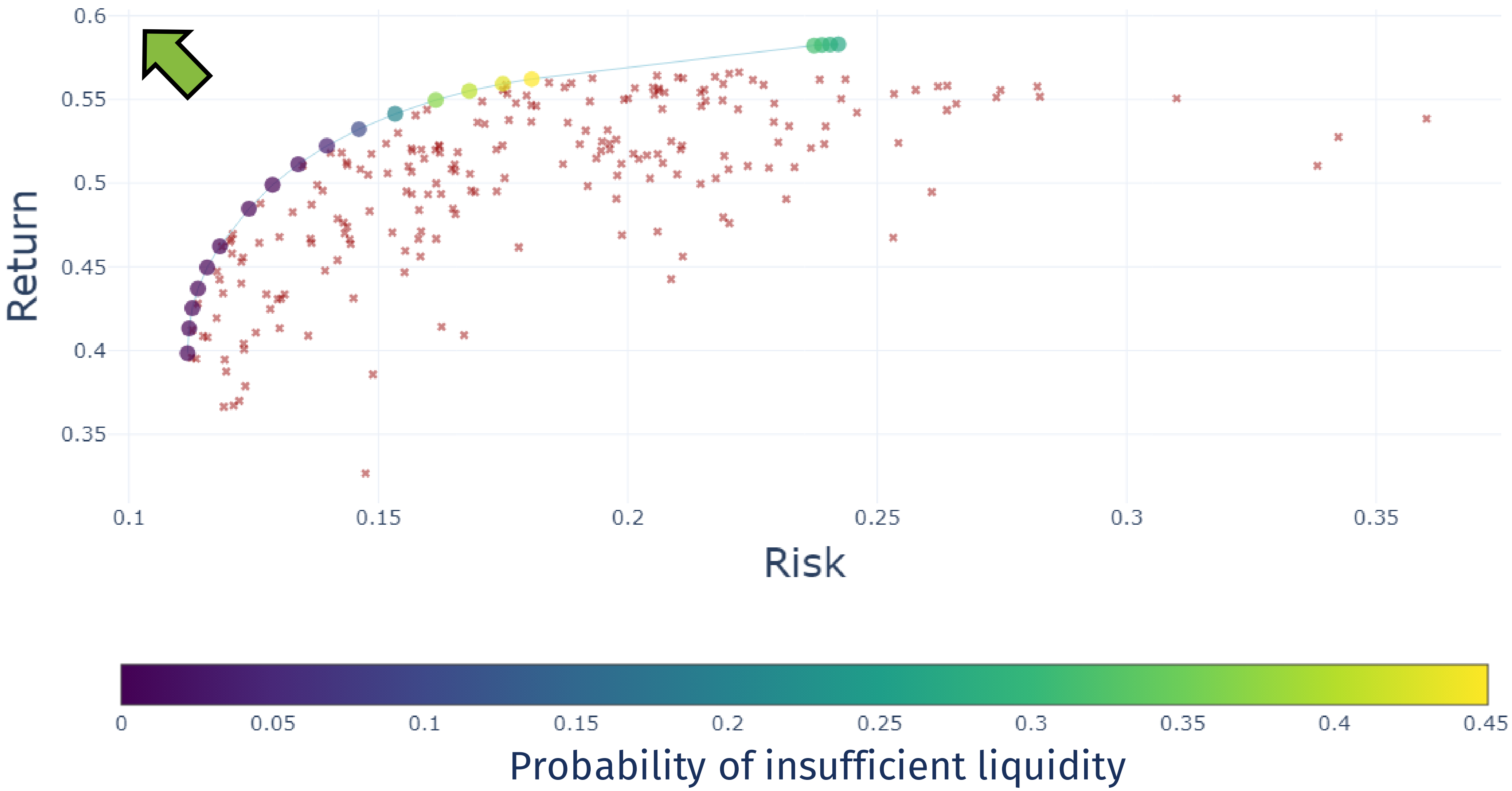
Liquidity risk scenario modeling

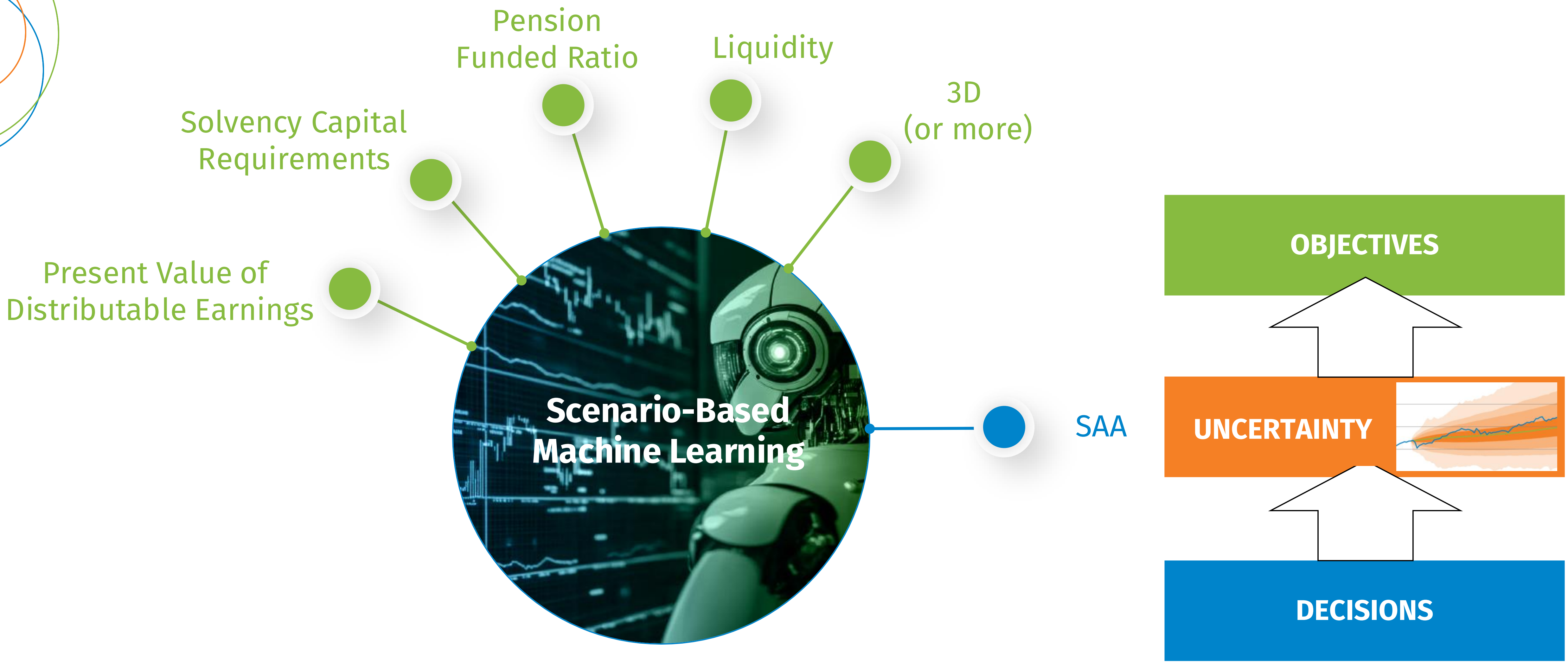
- Stochastic scenario approach used to model asset and liability cashflow dynamics, including PE capital calls and distributions

- Optimization problem:
  - Objective: Maximize return and minimize probability of available liquidity < 0%,
  - Decisions: SAA portfolio weights
  - Constraints: Portfolio weights, diversification penalty, asset only risk not larger than reference portfolio



Liquidity risk along the efficient frontier




Pension
Funded Ratio
Liquidity
Solvency Capital
Requirements
3D
(or more)
Present Value of
Distributable Earnings
Scenario-Based
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SAA
OBJECTIVES
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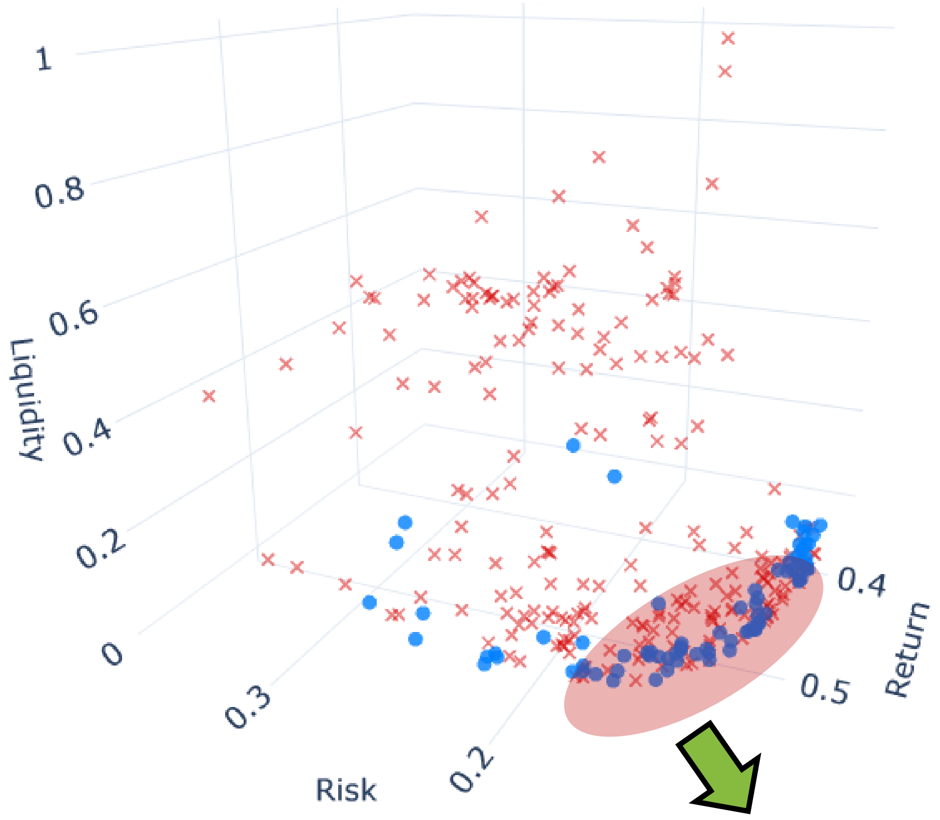
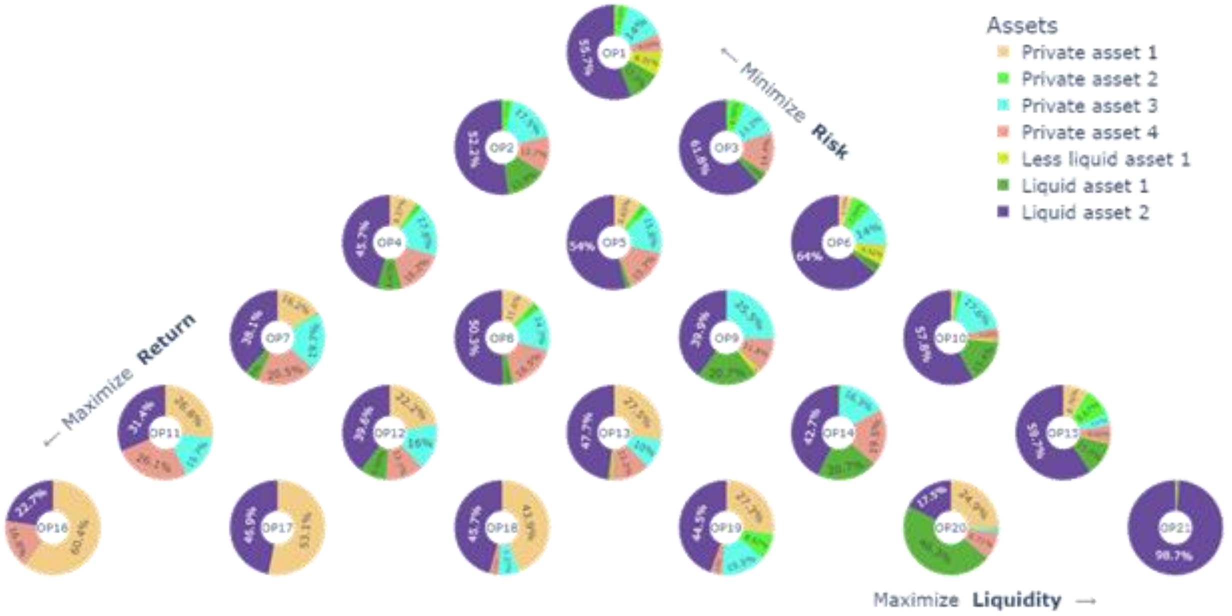
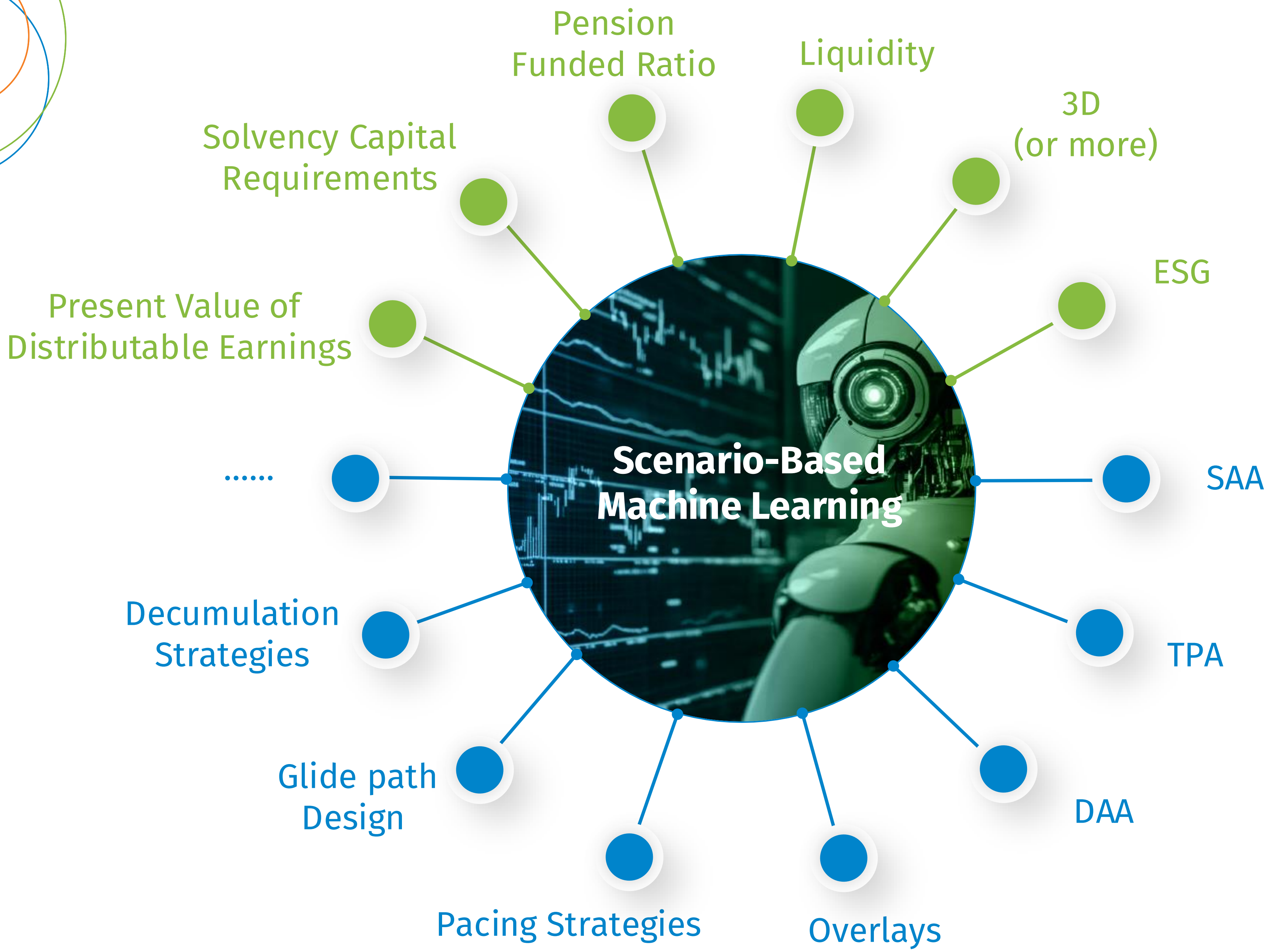
DECISIONS

3D optimization

And its visualization challenges






Pension
Funded Ratio
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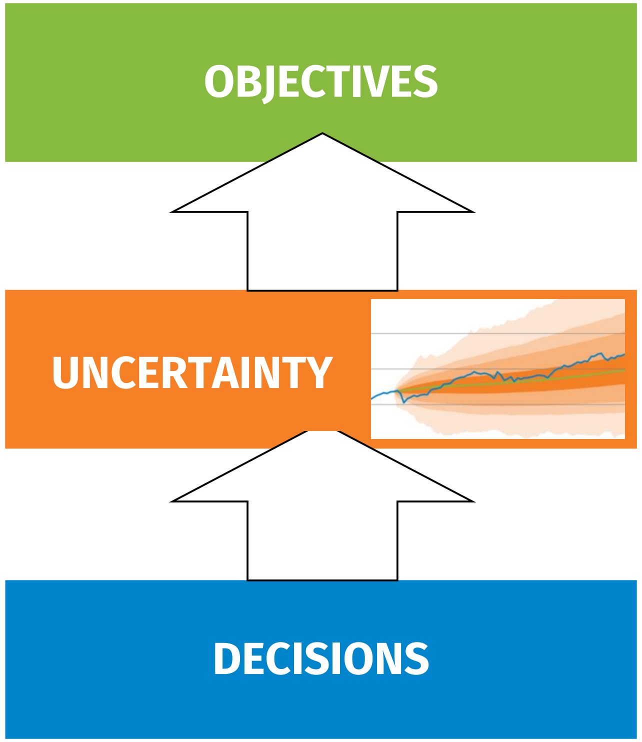
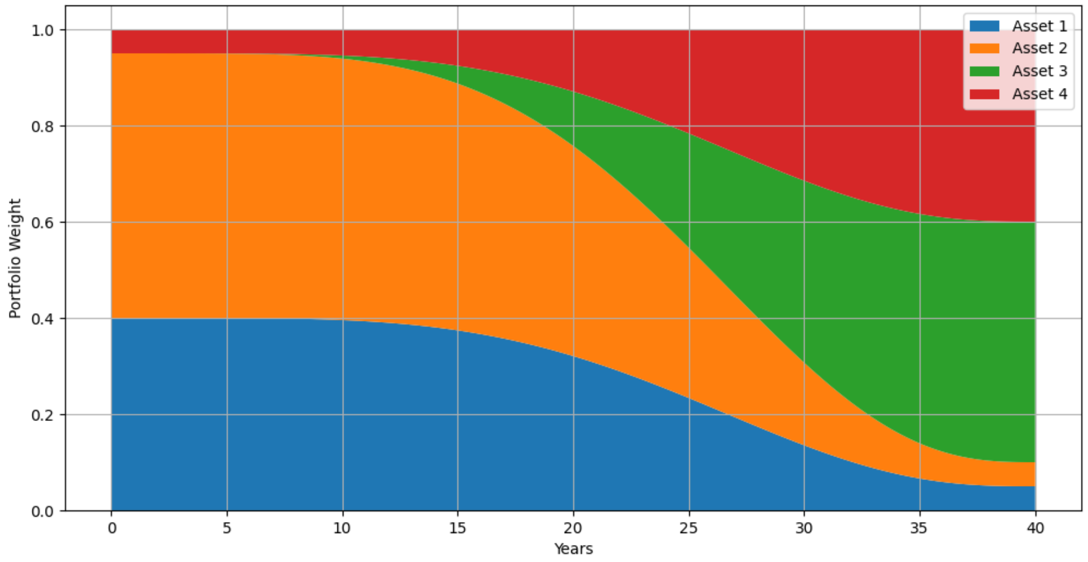
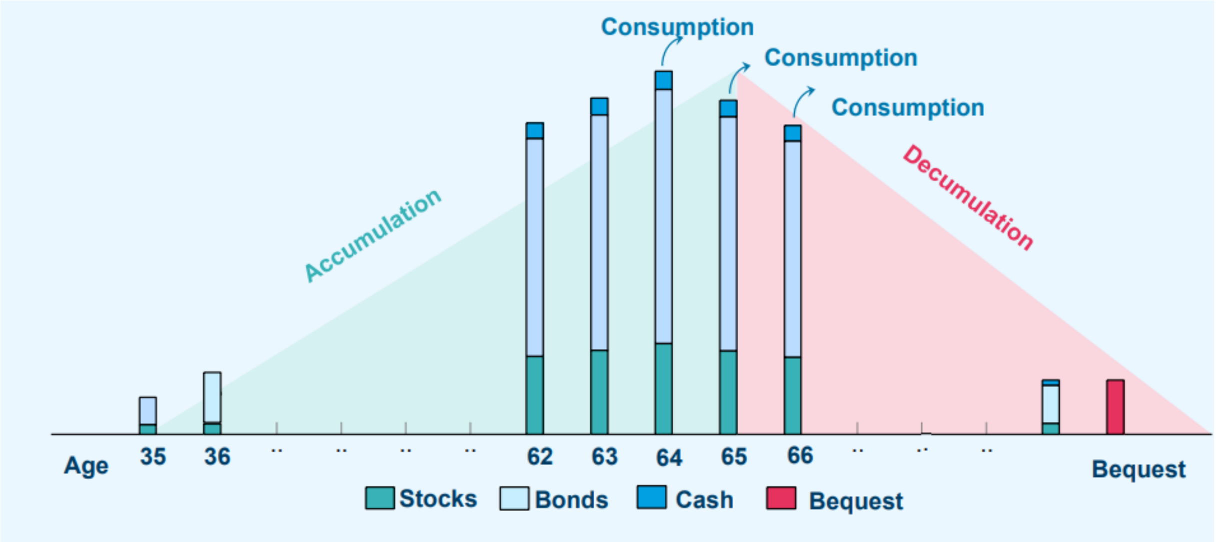
Solvency Capital
Requirements
3D
(or more)
ESG
Present Value of
Distributable Earnings
Scenario-Based
Machine Learning
......
SAA
Decumulation
Strategies
TPA
Glide path
Design
DAA
Pacing Strategies
Overlays


OBJECTIVES
UNCERTAINTY
DECISIONS

Glide paths and decumulation strategies

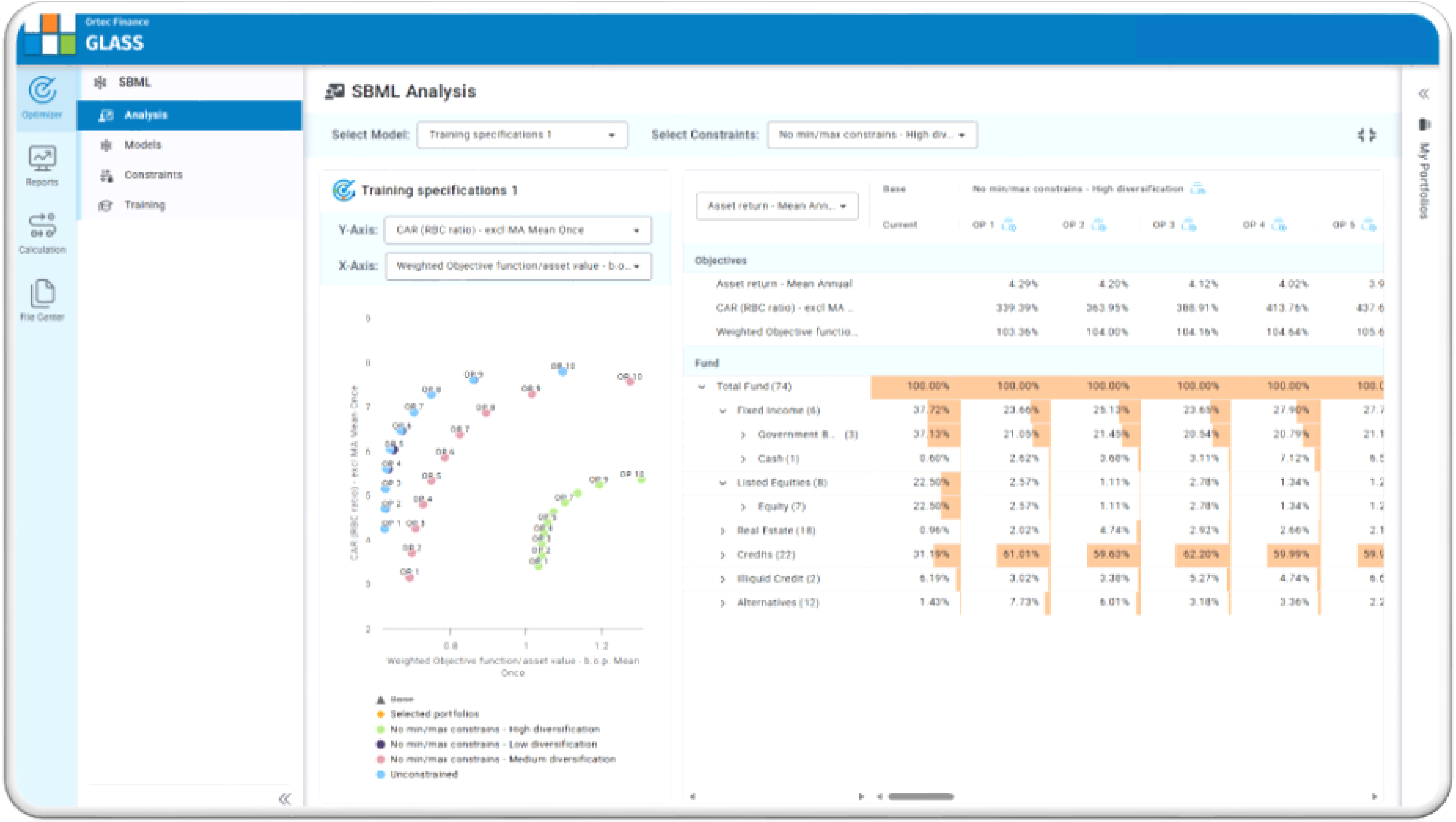
- SBML also usefully applied for
  - Designing optimal glide paths
  - Optimizing dynamic decumulation strategies





Source: Amundi Investment Institute, March 2024.

From theory to practice

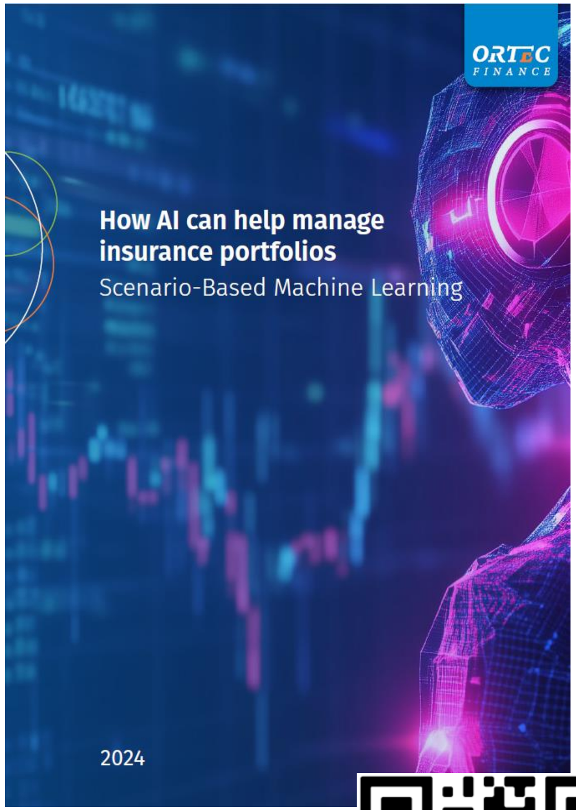


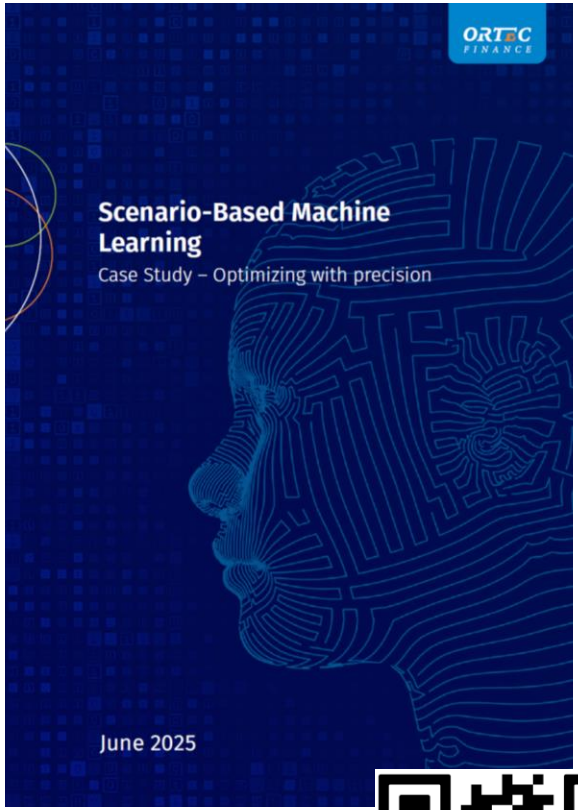
ML-augmented decision making

Final takeaways

- Although SBML allows for powerful optimization, the strategist must own the SAA process
- Human decision-making and explainability is a must
- Models can help investors but the framework in which the optimizer operates should be robust
  - Assumptions must be set in a structured way
  - Outcomes must be realistic and plausible, validated by users
  - Enable analysts to focus on “storytelling” and providing holistic advice

More information





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