ALM and Goal-based investing for retail business in the robo-advisory era

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Outline

The global scenario in financial advisory services

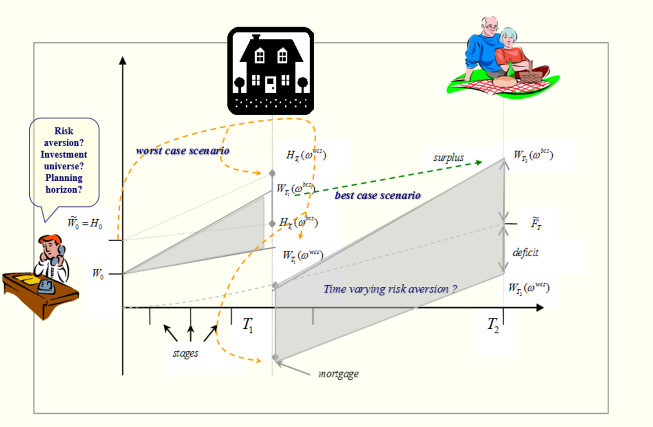
Personal and household financial planning services are moving into a new era, with far reaching implications, related to:

- The adoption of advanced **financial optimization** methods based on realistic assumptions and
- vehicled by client-oriented, **digital** online personal financial management tools, where
- individuals' **risk profiles** are associated with **goals-based investing** approaches.
- All three increasingly relying on advanced data analytics and **statistical learning** techniques, currently penetrating the field at different levels, as we will see briefly.

Indeed **individual ALM** is at the very crossroad of those forces. This area is attracting enormous interest in the ITC industry, the financial sector and by consulting firms.

Financial optimization: individual ALM and retirement

In 2005 we tackled the following goal-based household problem, which already encompassed several complex features:



Market of retirement products

Pension systems at OECD level are themselves undergoing a relevant transition towards more sustainable frameworks. We take the view of an intermediary delegated to manage individuals' financial planning problems. Under this assumption:

- Retirement wealth is considered as part of a long-term individual consumption-investment problem through the **life-cycle**
- Retirement products are consistent with increasingly popular DC-pension schemes and may take **hybrid features**,
- Return guarantees may be associated with pension products, whose payoffs are treated as for generic financial instruments but with relevant fiscal implications.

We don't go into the related (relevant) Institutional ALM problem of a pension provider, but stick to the individual perspective.

Comprehensive goal-based investing

The development of goal-based investment models in dynamic frameworks dates back several years. More recently we extended the goals classes to include:

- **Consumption goals** (car, college, journey) which do not add to individual wealth,
- **Investment goals** (real estate, gold, target returns) do increase when acquired the individual wealth,
- **Retirement goals** upon retirement to preserve living standards in real terms which can take the form pension fund or life insurance contracts
- **Protection goals** aimed at hedging from PC as well as life and healthcare events.

Individual ALM in practice: the foundations

Berger, A.J. and J.M.Mulvey (1998): The Home Account Advisor: Asset and liability management for individual investors. WTZ-JMM Eds C.U.P,

Consigli, G. (2007): Asset-Liability Management for Individual Investors, SAZ-WTZ Eds, North-Holland Handbook of ALM 2, Consiglio, A., F.Cocco and S.A.Zenios (2004):

www.PersonalAssetAllocation, Interfaces 34(4)

Kotlikoff L.J. (2008), Economics Approach to Financial Planning, The Journal of Financial Planning.

MacLean, L.C., Zhao Y, as W.T. Ziemba (2005): Wealth goal investing. In Wallace ad Ziemba Eds., SIAM series in Optimization

Medova, E.A., J.K.Murphy, A.P. Owen and K.Rehman (2008), Individual asset liability management, Quantitative Finance 8.6

Sharpe, W.F. (1998): founder of FinancialEngines, Inc., The Financial Engine Personal Advisor, www.financialengines.com

More recently ...

Consigli et al (2011, 2012, 2018) – just write to me

Dempster et al (2016, 2016, 2017) as we just saw ...

Martellini et al (2014, 2015, 2016) and so forth, see EDHEC's rich WP database

FINRA (2016) report on digital investment advice

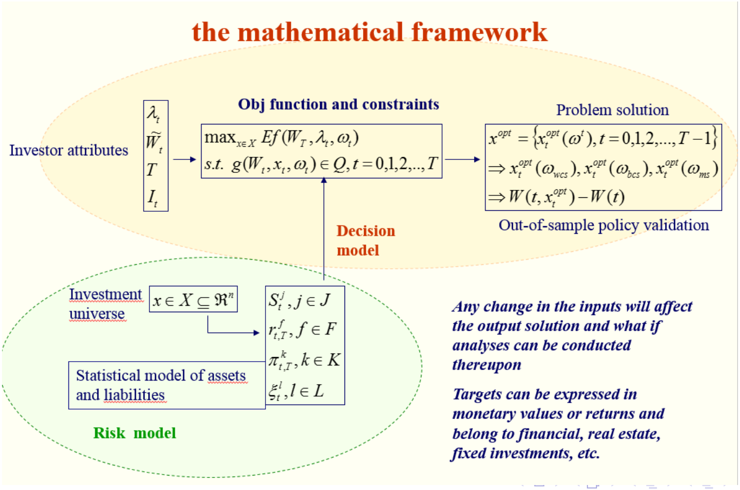
ORTEC Finance (2012) research on goal-based investments

IBM WM2016– EY2017 – PWC2017 data analytics and goal-based investment tools

Optimization and machine learning

- We like to distinguish between methodological implications of **ML techniques in optimization** and
- relevant ML-induced problem specific developments: these latter in our setting are very much related with the booming of the Fintech phenomenon.
- In the former group of specific interest the **learning** approaches that can be employed to limit or bound the approximation errors related to stochastic programming formulations.

Stochastic optimization 1



Stochastics

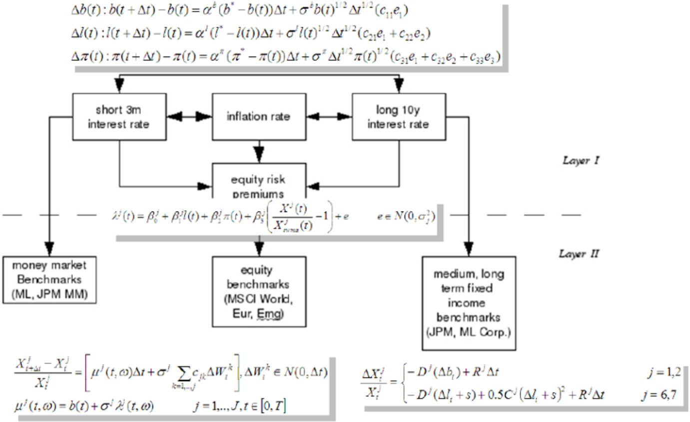


Figure: Long term scenario generation

Scenario Generation

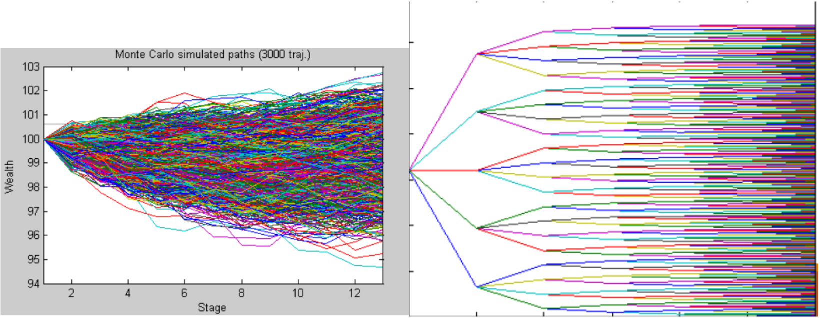


Figure: Scenario generation

Stochastic optimization 2

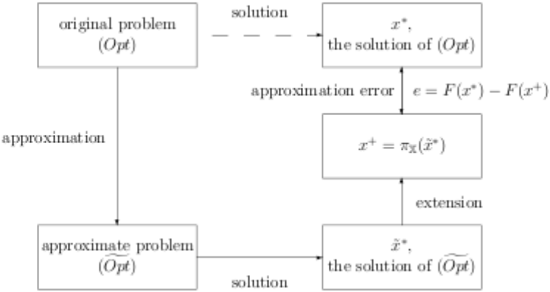


Figure: "True" versus approximate problem

Machine learning and optimal policy

We consider two areas in which ML methods can play a role in the formulation and solution of DSP problems.

- The definition of a suitable probability space from data collection,
- The extraction through **supervised learning** of optimal policies from the uncertainty model discrete approximation,

$$
\begin{aligned}
& \min_{\pi(x(\omega))\in\mathcal{X}} \rho(\omega, \pi(x(\omega))) && (1)\\
s.t. \quad & \pi(x(\omega), \omega) \quad \textit{non anticipative} && (2)\\
& g(x(\omega)) \in Q \quad \omega \in (\Omega, \mathcal{F}, \mathbb{P}) && (3)
\end{aligned}
$$

We distinguish in (1) the decisions x from the policy π determined by those decisions under a convex constraint region Q.

Scenario Generation

When approaching problem (1) we may exploit the distinction between the policy $\pi(\omega, x(\omega))$ and the decision process x. Then

- given a scenario tree and its associated optimal solution, we need to identify a mapping
- from that decision tree into a policy and we may rely on a learning approach: that policy is expected to be optimal with respect to the original true problem.

Typically for such step we rely on a clever combination of MC simulation and tree approximation.

Policy optimization

Several approaches have been proposed to infer an optimal policy from the solution of typically sequences of approximate MSPs:

- Mulvey and Kim (2011) consider the problem for an optimal portfolio problem
- In a DRO formulation, Kuhn et al (2011) analyse decision rules
- Defourny (2009) proposes an algorithm for policy evaluation from MSP through supervised learning.

Other criteria may be considered. Is this so new? Well ... indeed it sends us back to once celebrated **statistical decision theory** whose recent evolution cannot ignore data analytics.

The rise of online personal finance

- The industry of **online personal financial services** - aimed at determining individual optimal portfolios through web-based interfaces and ubiquitous access to investment decisions - is expected to exceed 2 trillion of USD within the next 2-3 years.
- The two largest providers of robo-advisory platforms manage already above 10 billion USD as at the end of 2016. In Italy MoneyFarm, recently awarded as best individual advisory service by the German Institute of Finance Quality, is growing year-by-year.
- Those platforms do indeed provide efficient web-based online interfaces but often, if not always, they rely even on long-term horizons on static asset allocation approaches and hardly capture a genuine **goal-based investment strategy**.

State-of-the-art, industry perspective

We may consider several dimensions in the delivery (through robo-advisory services) of dedicated investment solutions, related to a:

1. **Cost-efficiency**
2. **User-friendliness**
3. The adoption of **advanced optimization approaches** incorporating
4. a suitable **goal-based dialogue**.

Most currently available tools address with a sufficient degree of accuracy and effectiveness dimensions (1) and (even if with underlying limited modeling detail) (4) while (2) and particularly (3) are far from being properly captured.

Online personal finance and Robo-advisory

1	**Client on boarding**	▪ Mainly web-based communication campaign ▪ Communication to private investors (Retail) ▪ Ability to call the client service as a last resort ▪ Mainly digital clients' experience ▪ Registration 100% online (dematerialized supporting documents) ▪ Begins the customer journey by defining its savings plan
2	**Customer profiling**	▪ Determination of the investor profile carried out by an online form ▪ Dynamic in time, can request at each client's login if its situation has changed ▪ Potentially very sophisticated profiling and particularly suited to the personal situation of the customer (data science)
3	**Issuance of the advisory**	▪ Advice delivered via email, SMS or directly onto the personal space of the person ▪ Automatic advisory (no action required) ▪ Advice refined through the preferences criterion and the customer risk profile
4	**Monitoring**	▪ Daily monitoring ▪ Availability 24/7 online ▪ Graphics easily understood by the users / clients ▪ High transparency vis-à-vis the expenses and profits

The strength of robo-advisors lies in their ability to deliver an enhanced user experience

Figure: Claimed robo-advantages

Online personal finance and Robo-advisory

Figure: Accenture 2016 industry assessment

Individuals' risk profiling

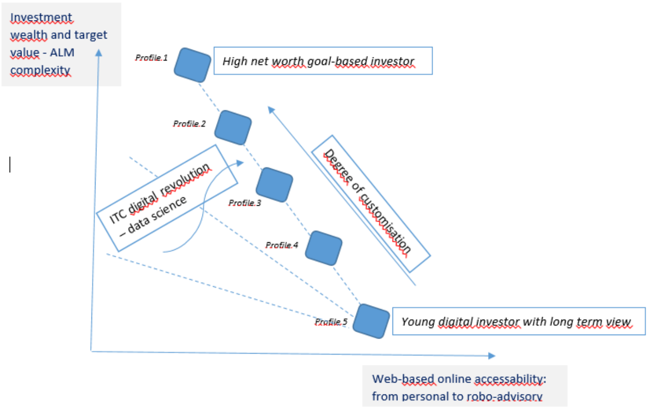
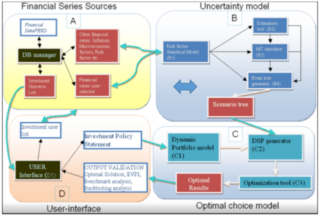


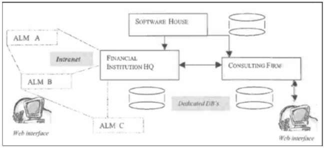
Figure: Digital development and individual ALM

Generic implementation framework

DSP internal view and interfaces-- 4-elements modular structure



Web-based financial services require fast computations and extremely fast and robust user-interfaces, able to map selected and relevant news into the investor's decision space and adapt her risk profiles



Sequential and smart learning procedures may significantly improve the performance of optimal risk control strategies and anticipate with dedicated signals markets' reversals and cycles.

Investment policy statement

Investment Policy Statement					
Case problem					
Family	**Father**	**Mother**	**Son**	**Daughter**	
Annual gross income	60.000	20.000	0	0	
Gender	M	F	M	F	
Age	45	38	14	10	
Financial strategy-constraints			Other Informations		
X(0)	150.000		Inflation-adj return		disable
Liquidity constraint	20.000		Max nominal loss p.y.		disable
Annual living costs	40.000		Max equity pos		disable
Target description	**year**		Type		amount
Real estate	10		Leveraged Invest.		250.000
College	5		Self-fin. Consump.		25.000
Music school	10		Self-fin. Consump.		15.000
Car	7		Leveraged Consump.		20.000
Car	15		Leveraged Consump.		20.000

Figure: Investment policy statement

ALM model

$$\max_{x \in X} \left[(1-\lambda)\mathbb{E}[W_T] - \lambda \sum_j \mathbb{E}_{\tau m} \left[\Psi_{\tau m} | \Psi_{\tau m} < \widetilde{W}_{\tau m} \right] \right] \tag{4}$$

S.t. for $s = 1, .., S$, $t \in \mathcal{T}$, $h < t$, a.s.:

$$\begin{aligned}
x_{k,0} &= \mathring{x}_k + x^+_{k,0} - x^-_{k,r,0}(1 + p_{k,r,0} + \varphi_{k,r,0}) \\
x_{k,h,t}(s) &= x_{k,h,t-}(s)\left(1 + r_{k,t}(s)\right) \\
&\quad - x^-_{k,h,t}(s)\left(1 + p_{k,h,t} + \varphi_{k,h,t}(s)\right) \\
x_{k,t}(s) &= \sum_{h \leq t-} x_{k,h,t}(s) + x^+_{k,t}(s) \\
y_0 &= 0 \\
y_{j,t}(s) &= y_{j,t-}(s) + y^+_{j,t}(s) - y^-_{j,t}(s)
\end{aligned} \tag{5}$$

ALM model ctd

for $s = 1, .., S$, $t \in \mathcal{T}$, $h < t$, a.s.:

$$
\begin{aligned}
& I_t(s) - C_t(s) + x^+_{1,t-}(s)\left(1 + \zeta^+_t(s)(1 - \vartheta_1)\right) \\
& - x^-_{1,t-}(s)\left(1 + \zeta^-_t(s)\right) - x^+_{1,t}(s) + x^-_{1,t}(s) \\
& + \sum_{k \in \mathcal{K}_3} \sum_{h} A_{k,h,t}(s) + \sum_{k \in \mathcal{K}_1} x^-_{k,t}(s) + \sum_{k \in \mathcal{K}_2} \sum_{h<t-} x^-_{k,h,t}(s) \\
& - \sum_{k \in \mathcal{K}} x^+_{k,t}(s) + \sum_{j=1,2} y^+_{j,t}(s) - \sum_{j=1,2} y_{j,t-}(s) b_{j,t}(s) - \sum_{j=1,2} y^-_{j,t}(s) \\
& = \widetilde{W}_t(s)
\end{aligned}
\tag{6}
$$

$$
\begin{aligned}
l_k X_t(s) &\leq x_{k,t}(s) \leq u_k X_t(s) \\
X_t(s) &\geq (1 - \epsilon) X_{t-}(s) \\
0 &\leq y_t(s) \leq \gamma \widetilde{W}_t(s)
\end{aligned}
$$

Optimal implementable decision

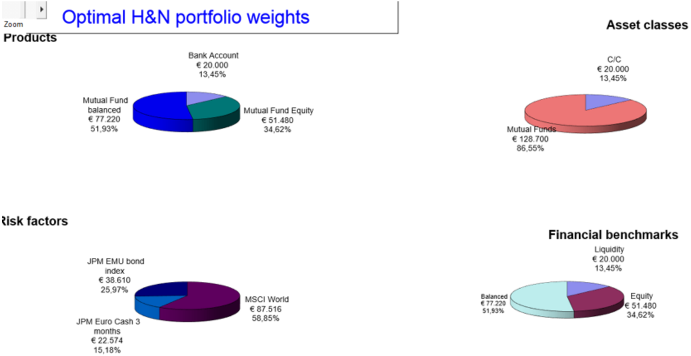
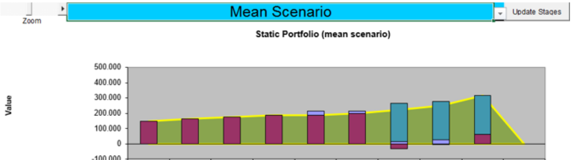


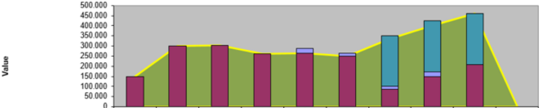
Figure: 4 views of the implementable decision

Scenario analysis



	0	1	2	3	5	7	10	15	20	
Wealth+Cumul.Targets+End Effect	150.000	162.546	175.120	188.020	188.595	198.803	221.539	252.294	315.559	0
Cumulative Target Investments	0	0	0	0	0	0	251.504	252.727	253.831	0
Targets (Consumption)	0	0	0	0	25.206	15.111	15.090	25.122	0	0
wealth	150.000	162.546	175.120	188.020	188.595	198.803	-29.965	-433	61.729	0
scale	462.140									

stage



	0	1	2	3	5	7	10	15	20	
Wealth+Cumul.Targets	148.700	299.539	302.043	261.510	264.238	248.854	336.920	400.353	462.140	0
Cumulative Target Investments	0	0	0	0	0	0	251.504	252.727	253.831	0
Targets (Consumption)	0	0	0	0	25.206	15.111	15.090	25.122	0	0
Adj. Wealth	148.700	299.539	302.043	261.510	264.238	248.854	85.416	147.626	208.309	0
scale	462.140									

stage

Scenario analysis

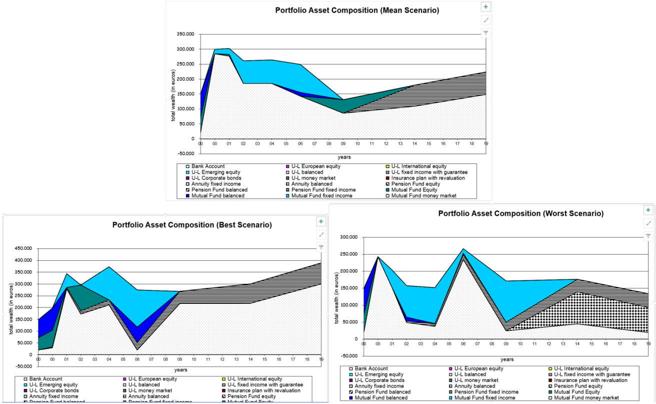


Figure: Product diversification

Goals attainability analysis

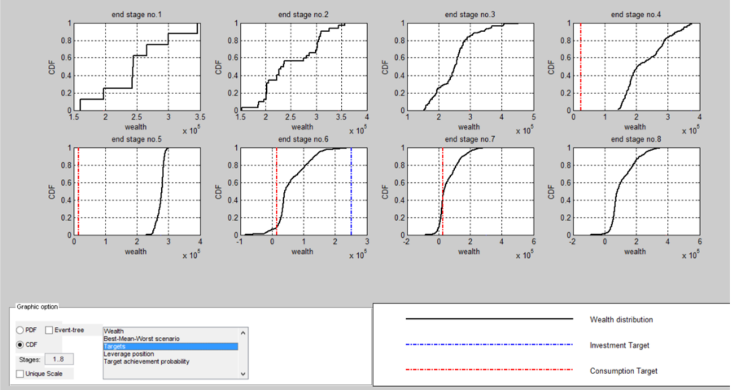


Figure: Goals wrt wealth distributions

Goal-based investing

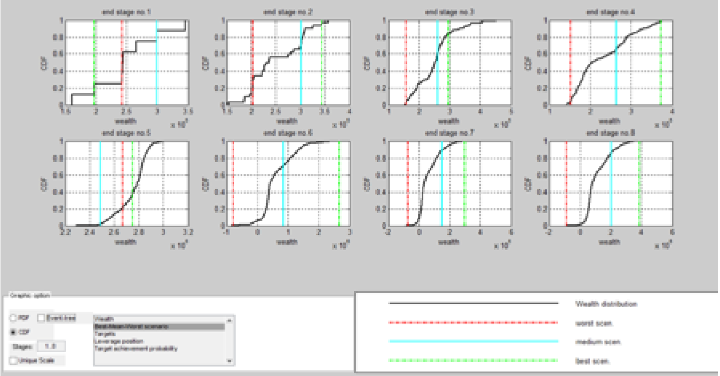


Figure: Wealth distribution at each stage

Summary evidences

- Significant and effective portfolio diversification over the first few years with good return generation across most of the scenarios
- Liquidity and self-financed acquisition of consumption goals and leverage for real estate
- Decreasing attainability of the ambitious retirement goal as financial scenarios do not allow relevant gains
- Pre- and post- real estate acquisition analysis leads to rather different portfolio strategies based on liquid mutual funds instruments first and liquidity and then retirement based policies

.

Conclusion

- Long term individual asset-liability management (ALM) falls in a problem class which at industry level is attempting to integrate recent digital developments
- MSP formulations of the problem are expected to increasingly rely in the future on ML techniques
- ALM optimization approaches and online personal finance developed somehow independently in the OR-MS community and the financial services progressively incorporating the benefits of digital power.
- The recent expansion of the **robo-advisory industry** requires now a convergence based on a revised information paradigm exploiting big data analytics.

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