Modern Risk Management in times of Machine Learning

by Dr. Denisa Čumova, FRM, Head of Portfolio Management and Quantitative Research &
Dr. Philipp J. Kremer, CAIA, Senior Portfolio Manager & Quant Researcher
La Francaise Systematic AM

Completed
05 | 2023.

ARTIFICIAL INTELLIGENCE METHODS IN ASSET MANAGEMENT

The launch of ChatGPT by Open AI at the beginning of the year highlighted **the revolutionary character of artificial intelligence methods**. While artificial intelligence was already present in translation services, digital assistants in customer chats, as well as image and speech recognition in medical science, ChatGPT has further revealed the variety of applications of artificial intelligence in our everyday lives.

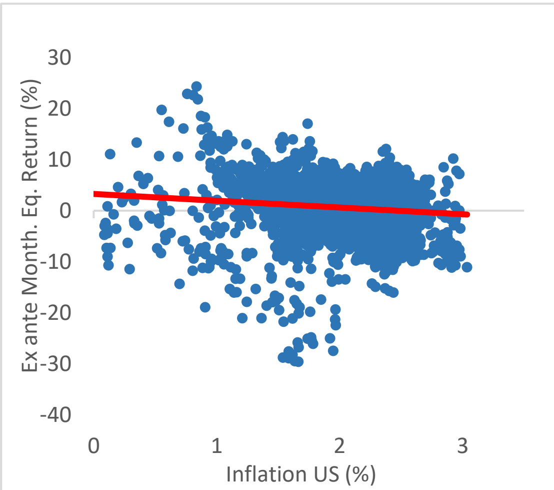
In the asset management industry, adopting Machine learning techniques can **contribute to optimizing the investment process and can ameliorate risk management**. **Machine learning (ML),** as a subfield of Artificial intelligence (AI), refers to **algorithms and models that can learn complex patterns from input data in order to make predictions**. Hence, ML methods can provide new insight on how to capture and evaluate capital market drivers.

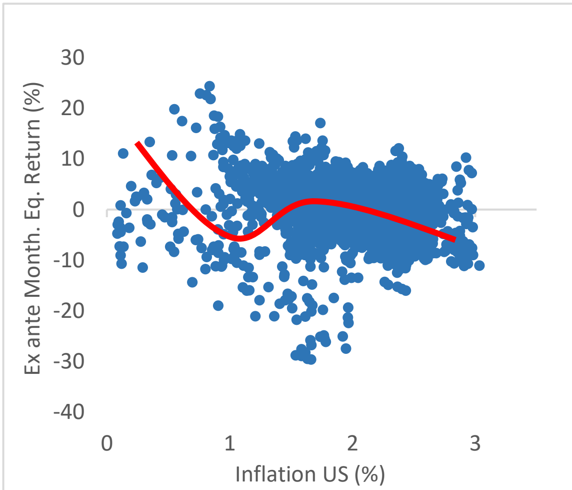
ML algorithms can model complex capital market relationships more precisely and can respond more dynamically to changes in market environments than traditional quant models since the structure of ML models is derived from input data. However, as ML methods are demanding with regard to data and computing power, they have for a long time not lived up to their full potential, despite the fact that the first models date back to the 1980s.

For the asset management industry, the solution to these limitations was resorting to a linear world, utilizing economic models such as the Capital Asset Pricing Model or the Arbitrage Pricing Theory, where the return and risk of an asset depends linearly on a set of factors. While the interpretability of such models is simple, economic reality reveals that relationships among variables are inherently non-linear in nature and that many non-linear economic relationships are not properly captured by traditional econometric models. Figure 1., where monthly US equity returns are plotted against US breakeven inflation rates, illustrates such a relationship. Clearly, a non-linear model is superior in capturing the underlying relationship.

FIGURE 1: Linear vs. Nonlinear Models

The figure plots the ex-ante monthly equity returns (in%) versus the US Inflation rate (in %). The left plot shows the fit of a linear model to the provided data, while in the right figure a nonlinear fit is chosen.





Source: La Francaise Systematic Asset Management GmbH; Bloomberg; Own calculation, MSCI USA Index, US Breakeven inflation 10 year (06/2006 – 03/2023)

Modern time risk management thus needs to utilize methods that **capture the complex nonlinear relationships between input data and trading signals, while considering the potential interaction effects**. At the same time, the system should acknowledge that **behavioural factors continue to play a crucial role** in the state of the market. One of the most well documented factors – the momentum factor – builds on the observation that market participants behave irrationally, following herding and overconfidence patterns, and thus creating excess return possibilities.

ML models can be used to identify **existing relationships among broad data sources while accounting for behavioural components including trend and volatility analysis**.

ML models do offer a solution to the nonlinear problematic. However, using only price data is detrimental when training machine learning tools, given their low signal to noise ratio. Using such data in complex statistical models can easily lead to overfitting and inferior out-of-sample performance. The upgraded system should therefore integrate **multiple global indicators, empirically validated, including price, fundamental, macro and sentiment data**. A **global focus** further allows the system to recognize that globalization has led to stronger cross-border economic linkages and increased financial integration between economies and asset classes. Macroeconomic shocks in one country are increasingly likely to spread to other countries. Hence, investors cannot simply rely on knowing the developments in their preferred market, but also needs to monitor major developments in other economies.

POOLING STATE OF THE ART MACHINE LEARNING MODELS

The model pooling approach acknowledges that no single model systematically outperforms any other. Associating multiple models, i.e., Support Vector Classifiers, Logistic Regression with a Regularization Penalty, Decision Trees, Neural Networks or Extreme Gradient Boost Classifier, allows to compensate for the limitations of a single one and to arrive at a more robust forecast. **The final pooled models generate a risk indicator defined as the probability of significant loss, from which the equity investment exposure for the overlay system is derived.**

The **calibration or training of ML models by quant researchers** is an important and necessary step. In fact, we understand the application of ML models as a technique to uncover the interaction among input variables utilizing the experience of seasoned investment professionals. For example, by identifying historical periods of significant loss and choosing a subset of possible algorithms, the selection and calibration step represents the true added value of the quant researcher, as it demystifies the black box character of ML methods and adds transparency, making the decision recallable regarding the input data and algorithms used.

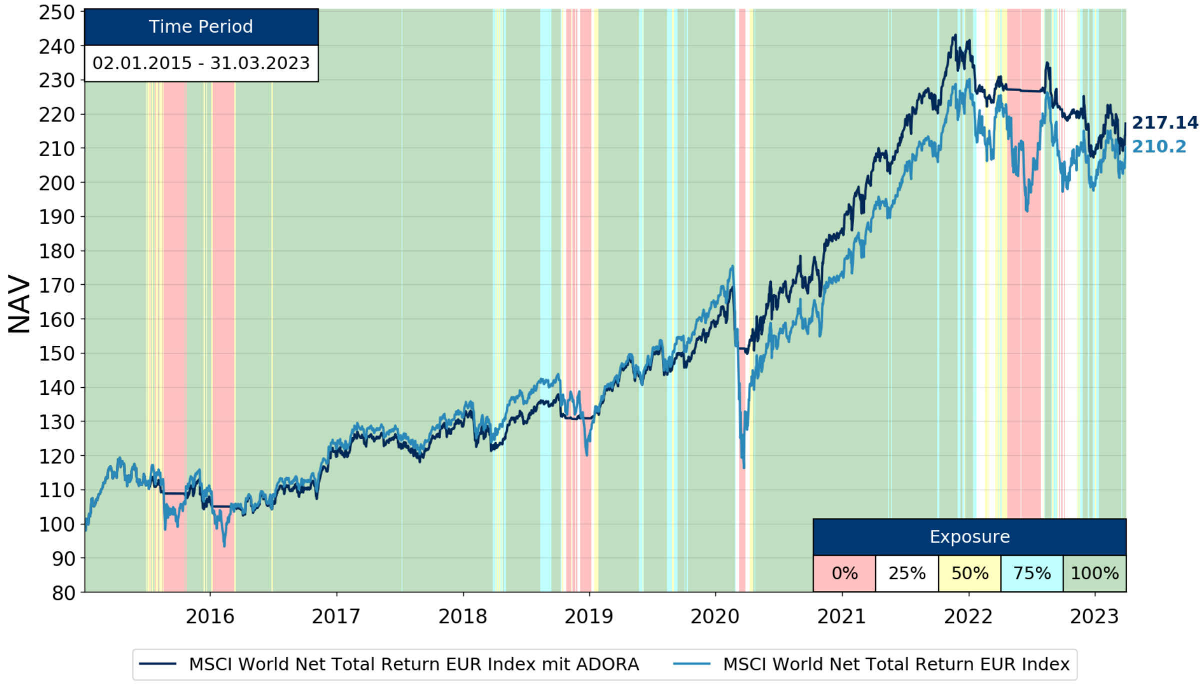
ML models should be trained and validated using input data over extensive periods of time. The objective is to select those models that show the best accuracy on the rolling validation sets - model performance on previously unseen data - while at the same time having the lowest model variance.

PUTTING THE PIECES TOGETHER

Each crisis has its own characteristics, duration and means of recovery. It is thus necessary that a modern-day risk management tool have the **flexibility to adjust to various stress scenarios**. It also ensures that the model is not overfitted to individual historical situations.

Figure 2. shows the performance of a pooled ML model developed by La Française Systematic AM utilizing the MSCI World Net Total Return EUR Index over a period running from January 2015 to March 2023 and comparing it to a traditional buy-and-hold strategy. As illustrated in Figure 2., the system considers five different investment states, whereas the generated signal allows to not only adjust exposure gradually, but also to dynamically react to sharp drawdowns and recoveries. Over the considered time period, the model reliably reduces losses in bear markets, achieving the most important requirement for risk management. At the same time, it allows to reduce the cost associated with a classic overlay strategy, by showing a similar performance to the buy-and-hold strategy, even yielding a superior risk adjusted performance. *Models may not always behave as expected and do not guarantee reduced losses. Performance is not guaranteed.*

FIGURE 2: Simulated performance of pooled ML model



* Since 01/2015.
Source: La Francaise Systematic Asset Management GmbH; Bloomberg; Own calculation based on MSCI World Net Total Return EUR Index; Past performance is not indicative of future performance.

CONCLUSION

The growing complexity of financial markets requires an agile risk management system that integrates broad data sources, while considering complex nonlinear relationships and interactions in financial data. State-of-the-art machine learning models combined with traditional well-proven behavioural models can detect endogenous shocks early by dynamically responding to the changing market environment. In the case of the model developed by La Française Systematic AM and when compared to a buy-and-hold strategy, the empirical analysis reveals significant loss reduction potential and an improved risk-return ratio.

INFORMATIVE DOCUMENT FOR PROFESSIONAL INVESTORS
This commentary is provided for informational and educational purposes only. Past performance is not indicative of future performance. The opinions expressed by La Française Group are based on current market conditions and are subject to change without notice. These opinions may differ from those of other investment professionals. Published by La Française AM Finance Services, head office located at 128 boulevard Raspail, 75006 Paris, France, a company regulated by the Autorité de Contrôle Prudentiel as an investment services provider, no. 18673 X, a subsidiary of La Française. La Française Systematic Asset Management GmbH has been licensed to conduct investment business by the Federal Financial Supervisory Authority (BaFin) and is registered in the Commercial Register under the registration number HRB 34125.

LA FRANÇAISE
INVESTING TOGETHER

128, bd Raspail 75006 Paris - France
Tél. +33 (0)1 44 56 10 00
Fax +33 (0)1 44 56 11 00

www.la-francaise.com