Machine Learning on Tactical Asset Allocation with Machine Learning and MATLAB Distributed Computing Server on Microsoft Azure Cloud

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Contents

• Motivation

• Market Factors & Data Interpretability

• Question to Machine & Learning Algorithms

• Using MATLAB Distributed Computing Server (MDCS) cluster on Azure

• Q & A
Purpose of this presentation

• What are the key elements in such an Investment Process:

  – The product profile (TAA, SAA, Absolute Return, Smart Beta)

  – The factors that define our market regimes

  – The question to the Machine

  – How the various algorithms identify the associations between regimes and assets performance

  – High Performance Computing

• Is it that simple? Challenges and rewards
Why Machine Learning

The problem

- Financial time series can be separated by inputs (factor drivers) and outputs (assets performance).
  The cause-effect relationships between them are non-deterministic, non-linear and multidimensional
- Professional investor’s task: Discover the relationships between economic events and market performance

The Solution

- Machine Learning ability: Discover nonlinear, previously unknown, associative structures within complex datasets
- The relationships between market inputs and outputs described by Machine Learning can then be seen as a behavioural pattern, proper for investment decisions: Buy/Sell, Long/Short, Overweight/Underweight.
Adaptive Machine Learning Investment Process

STEP 1: Client, Product
- Expected performance
- Accepted tolerance to core risk measures
- Allocation constrains

STEP 2: Investable Investment Universe
- Time horizon
- Trends and returns
- Correlations

STEP 3: Market regimes
- Drivers, Factors
- Noise, Signal
- Unbiased, Logic foundations

STEP 4: Machine Learning decision
- Structure + Out of Sample test = validation
- Best allocation match under current regime

STEP 5: Probability based allocation
- ML output = Class + Probability
- Used to construct the bespoke Product

Example on a TAA against Benchmark
- 55% Global Equities
  - 40% DM
  - 60% Emerging Markets
    - 60% EM
    - 45% EM Asia
    - 25% EM Latam
    - 30% EM Europe

STEP 6: Management
- Events monitored by the algorithms
- Performance and visualisation

Real time market analysis

High Performance Computing

Machine Learning Investment Committee
- kNN
- CaRT
- SVM
- NNs
Adaptive Machine Learning Investment Process

- The framework generates asset allocation decisions on traditional and alternative asset classes: equities, rates, credit, currencies, commodities and smart beta strategies for various factors (value, growth, carry, volatility, momentum).

- Several Machine Learners outputs are combined using advanced techniques to create one final coherent asset allocation and the corresponding trades.

- The use of high performance computing is a key technology for backtesting and live trading.
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Market Factors

• Factors are defined as explanatory variables that can drive markets performance.

• These factors must be:
  – **Comprehensive**: Include all necessary elements to identify a market regime.
  – **Explainable**: Based on solid research foundations.
  – **Persistent**: Their presence and influence is observed during different market cycles.
  – **Accessible**: Easily available to make the process reactive to the most updated information and maintain its continuity.

• Quoted factors: they include market participants expectations about future market events.

“**The 3m vs 10y T-Bill spread is a valuable forecasting tool, that significantly outperforms other macroeconomic indicators in predicting recessions two to six quarters ahead.”**

–Arturo Estrella and Frederic S. Mishkin, Federal Reserve Bank of New York

Source: Bloomberg
Data Interpretability

- Factors could be transformed using standardisation, clustering techniques that allow all algorithms to use as inputs the same information.
- These transformations allow for a better interpretability by the machine.
- Wavelet decomposition to reduce the risk of learning misguided by noise, with little loss of information.

Example: Money Flows into equity markets as a percentage of the country's index total capitalization.
Contents

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We focus on relative and absolute asset class performance trends over a defined time horizon, that is adapted according to the nature of the investment solution.

This way, our problem is a classification one, which allows us to use machine learning algorithms proved successful in the Artificial Intelligence literature.

The number of trades we generate depends purely on the Client’s/Product profile and return targets.
Definition of the problem is essential for the choice of the ML algorithm.

Multi-asset Funds are an example of a multi-class decision (many asset classes!). Due to the correlation among these classes, traditional single-label classification methods are not directly applicable.

When observing the trends of different asset classes, each instance is associated with multiple labels and the classes are not mutually exclusive but may overlap. In traditional multi-class (i.e., single label) an instance is only associated with a single label and, therefore, the classes are mutually exclusive.

Source: Bloomberg
Learning Algorithms

- $X = \mathbb{R}^d$ denotes the d-dimensional instance space,

- $Y = \{y_1, y_2, \cdots, y_q\}$ denotes the label space with q possible class labels.

- Task of multi-label learning: to learn a function $h : X \rightarrow 2^Y$ from the multi-label training set $D = \{(x_i, Y_i) | 1 \leq i \leq m\}$. For each multi-label example $(x_i, Y_i)$, $x_i$ is a d-dimensional feature and $Y_i \subseteq Y$ is the set of labels associated with $x_i$.

- Traditional machine learning algorithms adapted: k-Nearest Neighbours (kNNs), Decision Trees, Support Vector Machines (SVM), Neural Networks.

- Classification results:
  - Trade **Direction**: for any unseen instance $x \in X$, the multi-label classifier $h(\cdot)$ predicts $h(x) \subseteq Y$ as the **set of proper labels** for $x$.
  - Trade **Weight**: simultaneously, the answer returned by a multi-label learning system corresponds to a **real-valued function** $f : X \times Y \rightarrow \mathbb{R}$, where $f(x, y)$ can be regarded as the confidence of $y \in Y$ being the associated label of $x$. 
Now

- **Portfolios**
  - Tactical asset allocation
  - Systematic Global Macro
  - Tactical smart beta

- **Machine Learning**
  - Multi-label
  - Multi-class

- **AI Algorithms**
  - Ensemble methods
  - Support Vector Machines
  - Neural Networks

- **Data Management**
  - Clustering
  - Wavelet filtering
  - Market implied
  - Market news

- **Programming**
  - Object Oriented
  - Cloud computing

Before

- **Portfolios**
  - Risk on / Risk off
  - Equities / Bonds / Cash
  - Return vs Risk

- **Machine Learning**
  - Binary
  - Ternary

- **AI Algorithms**
  - Classification Trees
  - Support Vector Machines

- **Data Management**
  - Market priced
  - Macroeconomic surveys

- **Programming**
  - Scripting
  - Local cores
Computationally intensive ML algos

• The level of computing challenge is high. This is largely due to the jump in the volume of data being handled and the dimensionality / uncertainty involved in the analysis of a potentially-wide range of assets classes; each of which will require careful pre and post-processing to ensure the correct inputs for the algorithms.

• The inevitable level of uncertainty must be addressed and a robust statistical framework delivered around data selection and performance – something that is critical to the delivery of a tailored market view which will put a strain on the validation processes.

• All these need of an iterative back-test methodology highly time consuming for the computer.

• Support Vector Machines are a classic example of slow training, due to the quadratic programming problem they have to solve, with the number of variables equal to the number of training data.

• 5 years ago, our first implementation of the whole backtest process for this algorithm took 24 hours of computer time. Today, the picture is very different.
Contents

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The Challenge

• Since 2013 Emilio’s team used an MDCS cluster hosted on-premise in Scottish Widows Investment Partnership (SWIP)

• SWIP was then acquired by AAM and Emilio’s team were one of the first to migrate over to AAM platforms mid-2014

• An equivalent MDCS cluster capability had to be created in AAM as a prerequisite for Emilio’s team migrating over to AAM

• The technology teams had about 4 weeks notice to achieve this

• Lead times for procuring and installing new hardware on-premise upon which to install the MDCS cluster were prohibitive – due to the large size of the servers, something AAM was not setup to cater for

• A Cloud-based deployment was attractive for a number of reasons; not least the low cost due to infrequent usage of the cluster back then (a few hours a week)

• AAM had not directly used a cloud provider for the hosting of their own servers; this was unprecedented in AAM

• Due to AAM’s existing enterprise agreements with Microsoft, Azure was the only realistic option because the lead times for setting up such agreements with another cloud provider like Amazon were prohibitive

• But, MDCS was not formally supported on Azure nor integrated in any way (unlike Amazon EC2)…
Overview of AAM’s MDCS Cluster in Azure

Key Points:
• The Head and Worker Node Virtual Machines (VMs) are started when the cluster is required and stopped once no longer needed. This is done by the users using bespoke, in-house built Powershell scripts. The MDCS Windows Service (mdce) is auto-started on each VM and the cluster comes up in a handful of minutes.
• Fixed IP addressing used for VMs to ensure cluster comes up cleanly every time.
• No data is stored in Azure. Data passes from the Client Node to the Worker Nodes via the Head Node.
• Hosted License Manager utilised.
• DNS forwarding between Domain Controllers avoids needing to use FQDNs for the Azure VMs.
Conclusions

Benefits achieved

- Timely original delivery of the cluster capability – within the 4 week deadline. Faster than could have been achieved on-prem
- Low cost. <£10 per hour in Azure costs to run the cluster
- Self-service. Users can start & stop the cluster themselves using simple scripts
- Perfectly adequate speed/performance of algo execution

Limitations

- Start & Stop scripts rather simplistic and only run interactively with a user. Would be useful to be able to run in silent mode so that the Stop script could be called from within MATLAB upon completion of the algo execution, for example.
- One algo (LPPL) can’t run due to each worker process attempting to write to a file on the AAM fileshare but the segregated AD domains won’t permit this.
- Unable to combine our two MDCS licenses (of 64 and 16 workers) into one single cluster of 80. A limitation of using the Hosted License Manager over the on-prem FlexNet one.
Future opportunities

• Enhance StopCluster script so can be execution from within MATLAB upon completion of the algo execution

• Re-deploy the cluster into the fully-AD integrated Azure environment that AAM now has available and so retire the dedicated AD domain up in Azure

• Utilise emerging Azure VM Template from Microsoft which has MDCS pre-installed

• Codify the cluster setup – e.g., using Chef – so that other environments can be created and torn down at will. Such as for MDCS version upgrade testing, for example

• Industrialise some algo executions into Batch method and utilise Azure Batch emerging capability that Microsoft are working on providing
Thank you / Any questions?
Past performance is not a guide to future returns. The value of investments, and the income from them, can go down as well as up and your clients may get back less than the amount invested.

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