ENSEMBLE ACTIVE MANAGEMENT

AI'S TRANSFORMATION OF ACTIVE MANAGEMENT

JANUARY 2024

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I. Introduction

Since the turn of the century, actively managed US equity mutual funds have structurally underperformed their corresponding benchmarks at an undeniable level. Since 2000, based on 19,000 calendar year returns, these funds have failed to beat their benchmarks more often than they succeeded, delivering **only a 46% success rate**. For the most popular Large Blend funds, the results are even worse with a **41% success rate (59% failure rate)**[1].

This phenomenon has not gone unnoticed by investors: 18 consecutive years of net outflows for actively managed US equity funds, totaling in excess of $2.5 *trillion*[2].

The required performance leap to fix active management is not achievable through incremental gains. The gap is simply too large. Instead, the scale of the required step-change improvement demands a paradigm change, driven by new technologies and new approaches.

In 2018, the principles and investment justification of a new structural approach for building actively managed investment portfolios reflecting AI and Machine Learning techniques were introduced through an unheralded White Paper titled ***'Ensemble Active Management: The Next Evolution in Investment Management'***. That Paper provided data showing that Large Cap Ensemble Active Management ("EAM") portfolios were vastly superior to 'traditional' actively managed mutual funds in their ability to reliably outperform the S&P 500 index.

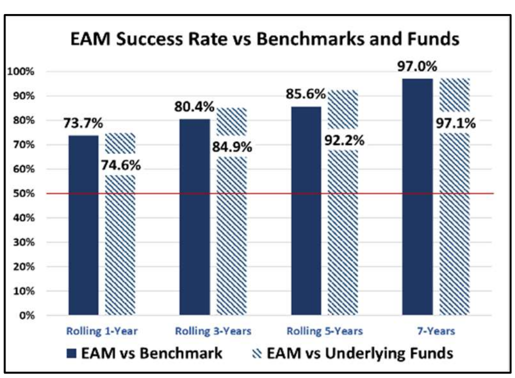
This White Paper updates that original study, and significantly expands upon it.

- The number of simulated EAM portfolios doubled to 60,000, generating 560 million data points.
- The underlying funds used within this study were expanded from 37 funds to 333, representing more than 140 fund families and $3 trillion in fund assets.
- The original investment coverage included just Large Cap mutual funds, while the 2024 White Paper added Small Cap portfolios and broke out results by style and capitalization.

One other important and tangible difference between the original 2018 Paper and the updated 2024 White Paper is that the current version underwent an **independent academic review of methodology, study design, and data integrity**. **That review substantiates the summary data and key conclusions of the White Paper.** The full Report is available as a companion document, and its Executive Summary is included in Appendix I.

EAM succeeds by applying the **proven mathematics of Ensemble Methods**, which are at the heart of nearly every major computational challenge in the world, to a multi-investment-manager foundation. Ensemble Methods ***improve accuracy in forecasting by mathematically integrating multiple predictive models while capturing areas of consensus agreement***. It has been called "the most influential development in Machine Learning in the past decade[3]."

The results are profound, and statistically significant. The chart to the left shows EAM **systematically outperforming both benchmarks and the underlying portfolio of funds**, with 1-year Success Rates (i.e., percent of rolling time periods where EAM outperforms) in the mid-70 percentiles, steadily rising to the mid-80 percentiles for rolling 5-year periods.



Many have wondered when AI and advanced technology would provide the long-awaited 'fix' for active management. This White Paper details the evidence of why Ensemble Active Management appears to be exactly that solution.

II. Ensemble Active Management Defined

EAM was never intended to incrementally improve a conventional, stand-alone investment portfolio. The industry has attempted this for decades, with limited results. Instead, EAM looked to where the rest of the world starts when solving the most sophisticated computational challenges – **a multi-expert platform integrated through the proven mathematics of Ensemble Methods**.

Ensemble Methods is one of the oldest and most trusted 'tools' within the AI revolution that improves accuracy in forecasting by mathematically integrating multiple predictive models. It is AI's version of the 'wisdom of experts', and driven by the consensus agreement of the underlying forecasting engines.

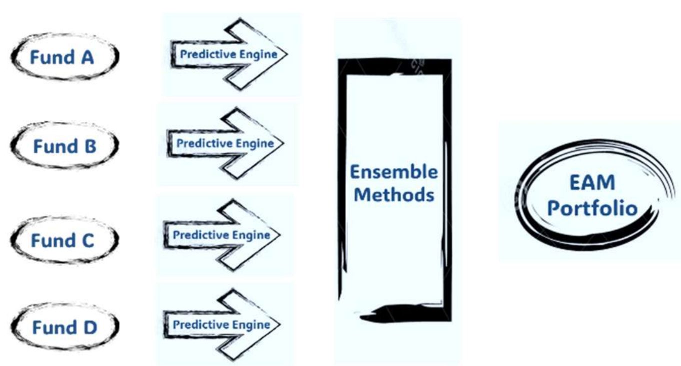
The key concept behind Ensemble Methods is the use of multiple predictive models, which are required for Ensemble Methods to add value. EAM's breakthrough came from the realization that embedded in all actively managed investment portfolios is a 'dynamic predictive engine.'

NOTE: Actively managed mutual funds can be easily viewed as predictive engines. The managers are trying to 'predict' which stocks will outperform. And substantial research shows that managers' highest conviction stock picks reliably outperform (see Section V, Identifying Manager Selection in Security Selection).

EAM became commercially viable after devising a means of extracting a fund's real-time predictive engine out of its holdings and weights (see Section V), opening the door to deploying Ensemble Methods techniques, and generating Ensemble Alpha.

Structural Design of EAM

Mechanically, EAM starts with the selection of 10 to 12 quality mutual funds. The **predictive engines are then extracted from the funds** (see Section V), which are then run through the Ensemble Methods mathematics. The final stocks are selected based on the consensus top picks of the underlying funds.

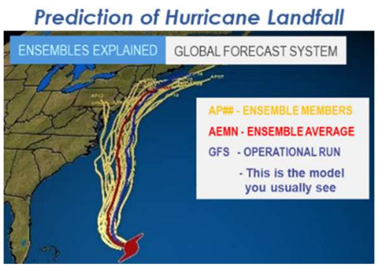


EAM can therefore be described as the **"consensus top picks of a dozen quality managers."**

The final result is a portfolio of approximately 50 stocks, with no derivatives, no leverage, and all holdings represented in the benchmark. And as demonstrated above, **EAM completely rethinks the paradigm for constructing active portfolios**.

III. Ensemble Methods – A Deeper Dive

Ensemble Methods are a time-tested, multiple-expert system designed to improve the accuracy of single-expert predictive algorithms or predictive engines. In their groundbreaking book *Ensemble Methods in Data Mining*[4], Seni and Elder defined Ensemble Methods as "**the most influential development in Data Mining and Machine Learning in the past decade. They combine multiple [predictive] models into one [that is] usually more accurate than the best of its components.***"*



One of the oldest uses for Ensemble Methods is for predicting hurricane landfalls (see redline, chart to the left). But hurricane landfall is just one example of Ensemble Methods. A search on *Google Scholar* for Ensemble Methods will return thousands of articles. The sidebar to the right provides a sampling of applications.

INDUSTRY APPLICATIONS FOR ENSEMBLE METHODS

Facial recognition;

Predicting service sector bankruptcy;

Cyber threat detection modeling;

Useful life prediction of aircraft engines;

Predictive modeling for lumbar spinal surgery;

Uncertainty analysis for climate change conditions;

Early-stage prediction of diabetes;

Uncertainty-aware reinforcement for self-driving cars;

Predicting irrigation groundwater quality;

Flash-flood propagation susceptibility estimation;

Predicting COVID-19 mortality;

MRI-based tumor detection;

Early autism identification;

Emergency prevention of hydroelectric power plant failure.

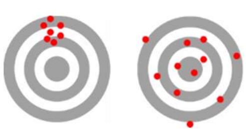
Why Do Ensemble Methods Work

The intuitive benefit of looking for consensus agreement from multiple established experts is obvious. Consider the following hypothetical:

> *Assume that an investor had direct access to three of the very best portfolio managers in the industry. Once a month that investor calls all of the PMs and asks for their five best stock picks. And (for the sake of this hypothetical), they all agree to provide that information. For this month, it turns out that two stocks appear as favorites for all of the PMs.*

Is there any question that those two 'consensus' stocks deserve ownership? This is exactly the principle behind Ensemble Methods. But Ensemble Methods are the industry go-to for complex machine learning problems, not just due to intuition, but based on proven mathematics.

As practitioners of Machine Learning know, the two most common errors impacting a predictive algorithm are 'Bias' and 'Variance'[5]. Bias occurs when the underlying assumptions in the predictive algorithm are flawed. A 'High Bias' predictor will generate results that are consistently off target (Figure below, on left). Variance refers to its accuracy. A 'High Variance' algorithm will deliver results with low accuracy (Figure below, on right).



All predictive algorithms have intentional and unintentional biases. And at a certain threshold, efforts to reduce bias will ironically increase variance[6]. This is referred to as the **Bias–Variance Conflict**.

This is where a multi-expert system using Ensemble Methods changes the dynamic. Without triggering a discussion of higher level math, one of the more digestible concepts is 'bias diversification'. Ensemble Methods actively link together multiple independent predictors, each with its own set of biases. Embedded diversification will allow the multiple biases to partially neutralize each other, creating a new solution with a smaller bias.

It is universally recognized that Ensemble Methods techniques are the most efficient tools within the universe of Machine Learning for solving the Bias – Variance Conflict.

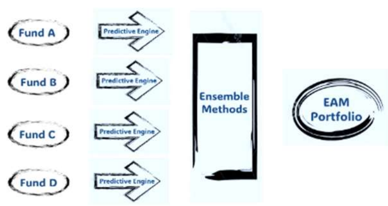
IV. Results

The White Paper results are presented in three categories, each focusing on different, yet critical insights.

1. **Validation of the existence of 'Ensemble Alpha'**. For EAM to act as a structural solution to the performance shortfall of traditional active management, a new and persistent alpha source is required.
2. **Validation that the amount of Ensemble Alpha generated enables highly persistent outperformance vs standard index benchmarks**. Outperforming traditional funds is the minimum threshold for active managers, but the true metric for active management success is outperforming passive investments/benchmarks.
3. **A look at risk management and distribution of tails**. Excess return is critical, but if it comes at the cost of excessive investment risk, that benefit can be ephemeral. This section looks at the risk of underperforming the benchmarks as well as the distribution of performance tails as seen via histograms.

Validation that 'Ensemble Alpha' Exists

As quoted by Seni and Elder in Section III, "Ensemble Methods [ ] combine multiple [predictive] models into one [that is] usually more accurate than the best of its components.[7]"



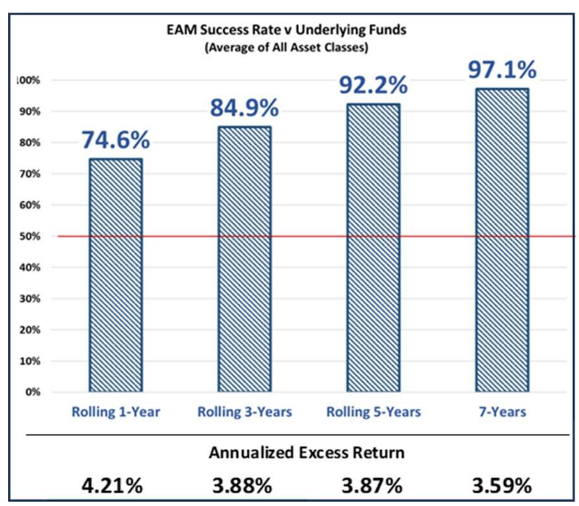
In practice, EAM works by feeding the stand-alone predictive engines from a dozen quality funds through Ensemble Methods techniques. The **alpha creation process** emerges from the mathematics of Ensemble Methods, taking the weak predictors of the individual funds and enhancing them into a strong predictor driving the EAM portfolio.

In plain English, the returns of the EAM portfolio should be statistically superior to that of the average of the underlying funds used to create the EAM portfolio, due to EAM's improved consensus-based decision-making. This performance 'lift' would be evidence of Ensemble Alpha.

Therefore, the most literal performance comparison demonstrating the existence of Ensemble Alpha will come by comparing returns from the 60,000 EAM portfolios to that of the corresponding underlying Portfolio of Funds (POFs) that were used to construct each EAM portfolio.

NOTE: EAM PERFORMANCE IS CALCULATED GROSS-OF-FEE (IDENTICAL TO INDEX CALCULATIONS) AND POF PERFORMANCE IS BASED ON PUBLISHED NET-OF-FEE RETURNS. THE MAXIMUM FEE CHARGED BY TURING FOR EAM PORTFOLIOS IS 25 BASIS POINTS (0.25%). ANALYSIS SHOWS THAT APPLYING THIS FEE DIFFERENTIAL HAS A NOMINAL IMPACT ON RESULTS. FOR EXAMPLE, ***THE SUCCESS RATE OF EAM WITHIN LARGE BLEND IS 71.5% GROSS-OF-FEE, AND WITH MAXIMUM FEE APPLIED IT IS 69.7%.***

This White Paper generated more than 30 million head-to-head comparisons between EAM and POFs over varying rolling time periods. These results are shown to the right.



<u>**Key observations**</u>:

The average Success Rate (SR) and annualized excess returns for EAM across all asset classes, as well as across all rolling windows, are well above the 'neutral' 50% threshold.

- The EAM SRs range from **75% to 97%.**
- Annualized excess returns range from **359** to **421** basis points.

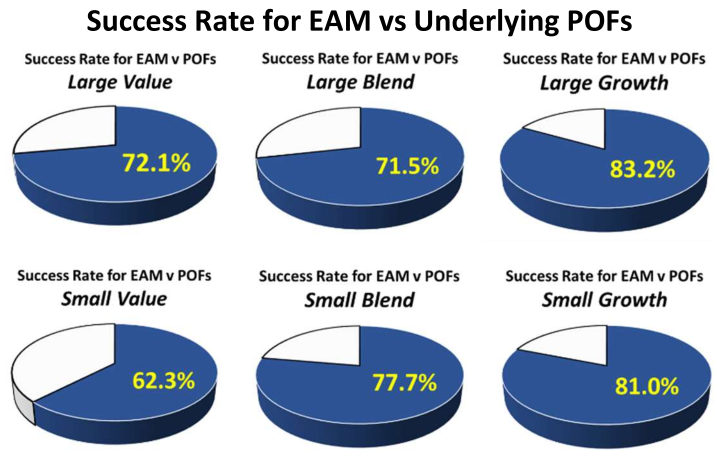
- As the rolling windows increase, the SR improves, demonstrating the statistical benefit of compounding.

This is a game changing level of outperformance – in terms of both persistency and scale – versus traditional active management. It also clearly indicates the formation of hundreds of basis points in new Ensemble Alpha.

Any viable alpha source needs to be deliverable across different capitalization levels and investment styles. This is the case for Ensemble Alpha and EAM.

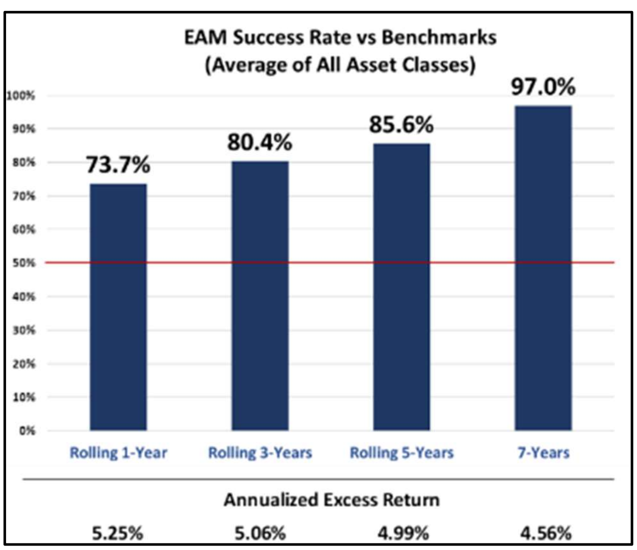
Not only was the average EAM SR for rolling one-year periods strong (75%, from chart on prior page), the results were mirrored through every one of the style and capitalization asset classes evaluated – a critical threshold demonstrating breadth of results.

This phenomenon can be seen in the series of six pie charts shown here, all detailing EAM SRs vs POFs for the six asset classes based on <u>rolling one-year periods</u>. As can be seen, the results are stable and strong for large cap and small cap portfolios, as well as for value, blend and growth styles.



Validation that the Amount of Generated Ensemble Alpha is Sufficient to Outperform Traditional Benchmarks

The last section evaluated EAM vs underlying funds to 1) validate the creation of Ensemble Alpha, and 2) to demonstrate that the created alpha engine is scaled (at hundreds of basis points in average size). This section focuses on EAM versus passive or index benchmarks.

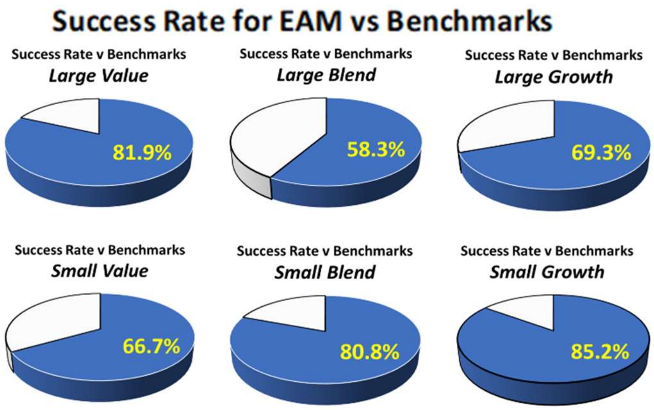


<u>Key observations:</u>

The results are profound, and are at a delivered threshold that would fundamentally 'flip the narrative' of active vs passive superiority. Averaged across all asset classes, EAM substantially outperforms standard benchmarks:

- Success Rates start at **74%** for rolling one-year periods, and increase to **86%** for rolling five-year periods.
- Annual excess returns range from **456** basis points to **525** basis points.
- As the rolling windows increase, the SR improves, demonstrating the statistical benefit of compounding.

This level of outperformance can have a dramatic impact on investors. For reference, a $1,000 investment, compounded for 25 years at 10% (standard long-term return of the stock market), grows to roughly $10,835. Increasing the annual growth rate by 5% (500 basis points), as implied by the EAM outperformance vs benchmarks, translates to a $32,919 final amount, or more than triple the 'standard' investment returns[8].



As mentioned above, any viable alpha source needs to be deliverable across different capitalization levels and investment styles.

As can be seen in the series of six pie charts shown here, all detailing EAM SRs vs benchmarks for the six asset classes based on <u>rolling one-year periods</u>, the results are stable and strong for large cap and small cap portfolios, as well as for value, blend, and growth styles.

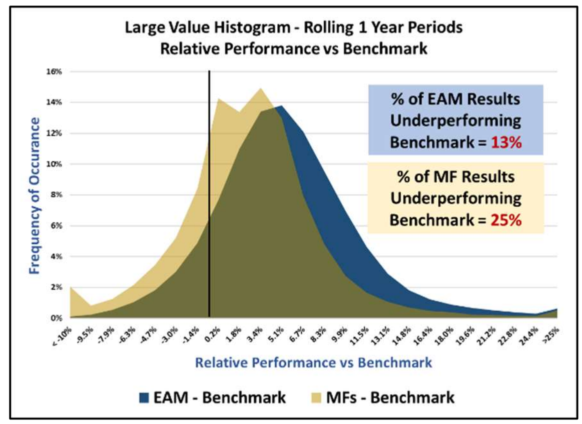
Risk Management and Distribution of Tails

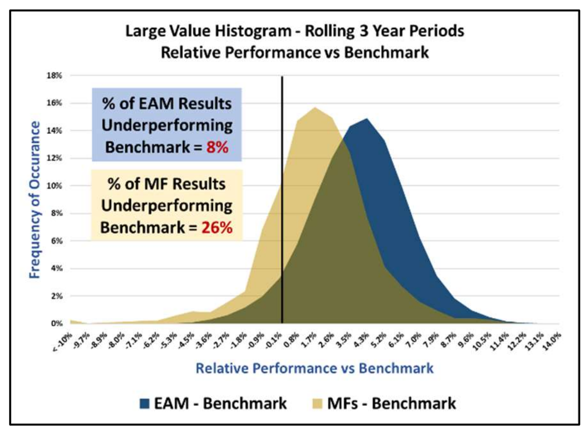
In this section, EAM portfolios are compared to the individual 333 funds that were used within this study, with a focus on tail events. The three charts to the right show histograms of relative performance results for the Large Value asset class, based on rolling 1-year periods (top), rolling 3-year periods (middle) and rolling 5-year periods (bottom). Large Value was selected as a representative sample set.

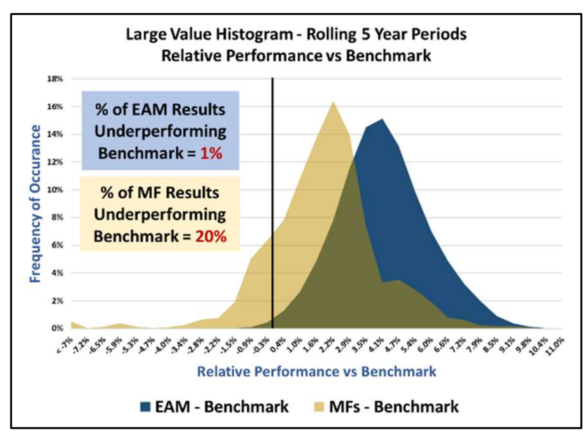
The dark vertical line in each chart reflects the 0% relative performance point. Thus all returns to the left of the 0% line represent underperformance, and to the right reflect outperformance. The dark blue shaded area is the distribution curve for EAM, while the amber area represents the distribution curve for mutual funds.

Key takeaways include:

- The percent of events where EAM underperformed dropped precipitously as the rolling window increased, from 13%, to 8%, to a negligible 1%.
- The percent of events where the mutual funds underperformed also declined as the window expanded, but less so, from 25%, to 26%, to 20%.
- In all scenarios, EAM had reduced negative tails as compared to the funds, and showed a positive shift to the right depicting improved overall performance.







In summation of this Results section, EAM portfolios delivered <u>superior performance on all three parameters</u>:

- ***Compared to the underlying POFs, EAM persistently outperformed, validating the existence of Ensemble Alpha.***
- ***EAM dramatically and persistently outperformed traditional benchmarks.***
- ***EAM portfolios were able to reduce tail risk vs mutual funds.***

V. Extracting the Predictive Engine from Mutual Funds

A critical breakthrough enabling the Ensemble Methods techniques within active management was the discovery of how to extract a mutual fund's predictive engine from its holdings and weights. The process is as follows:

1. Access, on a **real-time basis**, the fund's holdings and weights.
2. For all securities in the portfolio, determine the manager's level of expectations for performance versus the market – positive or negative. The most important element to extract is the level of a manager's '**conviction'**.

Hercules.ai™ – AI-Based Technology Enabling Real-Time Fund Replication

For EAM construction, fund holdings can be accessed through any means as long as the data is available on a real-time basis. For this White Paper, Turing used its **proprietary Hercules.ai fund replication technology** to access fund holdings for all funds evaluated. This technology replicates, on a real-time basis, daily holdings and weights of US equity funds using only public information.

The technology has been in live operation since 2016, and operates at more than a 99.4% accuracy level[9]. The current Hercules.ai database contains at least 4 years' worth of replicated data for actively managed funds, representing 95% of the applicable US equity universe.

Identifying Manager Conviction in Security Selection

The benefit of extracting predictive engines from mutual funds needs to be predicated on the assumption that, even though the entire class of active funds underperform on a net return basis, active fund managers can generate investment alpha (before fees and transaction costs).

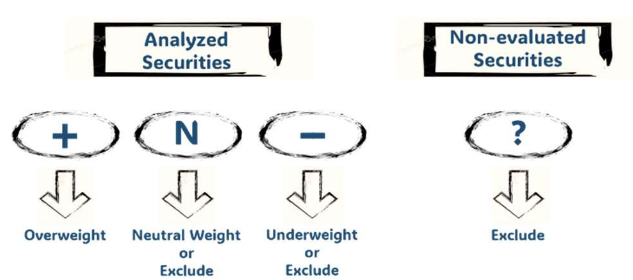
Fortunately, there has been a trove of academic research validating active managers' skill, at least regarding their best ideas/highest conviction stock selections:

- The concept of "Active Share" supports this thesis[10].
- The Paper "Best Ideas", 2005 [SSRN-id1364827], authored by Cohen, Polk, and Silli, concluded after an exhaustive research effort, "*We find that the stocks that active managers display the most conviction towards ex-ante, outperform the market, as well as the other stocks in those managers' portfolios, by approximately one to four percent per quarter depending on the benchmark employed*."[11]
- The CFA Institute published "The Active Manager Paradox: High Conviction Overweight Positions" in 2019 that concluded "*High-Conviction Overweights, composed of the managers' best ideas, is the only category that delivers stock selection alpha*."[12]

Managers' decisions regarding the securities available for inclusion in the portfolio emerge from four categories:

1. The security is **evaluated**, and 1.a) deemed likely to **outperform**, 1.b) deemed to **perform in line** with the market (or the manager was unable to make an informed decision), 1.c) deemed likely to **underperform**.
2. The security was **never evaluated**.

These four outcomes, when adjusted to reflect a manager's level of relative conviction (e.g., the stocks in grouping 1.a. above can be ranked from 1 to N), **comprise the prediction engine that drives that fund's performance**. The resulting decisions can be depicted in the chart to the right.



However, the weights of securities in a given portfolio do not directly reflect the manager's prediction engine – they are **distorted by risk management and tracking error constraints.** Mutual funds are generally required by regulatory guidelines, as well as industry convention, to 'track' reasonably closely to its benchmark. The idea is to outperform, but not to 'decouple' from the investment category. In practice, this means that the manager will typically start with the benchmark's weights, and then adjust them based on their level of conviction for each stock.

In practice, the manager translates their predictive engine into weights for the fund holdings as:

For example, as of September 30, 2023, Tesla (TSLA) was the 6th largest holding in the S&P 500 index at **1.9%.**

- If a manager expects Tesla to outperform, they would overweight it. The higher the conviction, the larger the overweight. Modest conviction might equal a **3% weight**, high conviction might equal a **5% weight**.
- If a manager is neutral, a likely weighting would be equal to the benchmark weight, or **1.9%.**
- If a manager dislikes Tesla, then the weighting might be **1%, or they would completely remove the stock**.
- If a manager never reviewed the stock, then the stock is **likely removed (or set to benchmark weights)**.

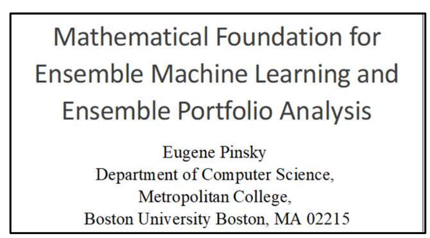
In order to extract the predictive engine, we need to reverse the process and remove the 'distortion factor,' which is the original benchmark weights. This procedure is shown in the chart to the left.

It is the resulting overweights and underweights from 10 – 12 mutual funds that are deployed within the Ensemble Methods mathematical 'engine' to generate the final EAM portfolio.

Mathematical Proof Validating EAM, and Mutual Funds as Predictive Engines

To be clear, **predictive engines are required as inputs to drive Ensemble Methods techniques**. Thus, the question of whether a mutual fund can act as the basis for predictive engines, and whether those predictive engines can properly power Ensemble Methods techniques, must be explored.

Fortunately, these questions were directly addressed by an academic paper published in June 2018 by Eugene Pinsky[13], a professor of Computer Science at Boston University. His paper, "*Mathematical Foundation for Ensemble Machine Learning and Ensemble Portfolio Analysis*", **provides a full mathematical proof demonstrating that Ensemble Methods, applied to predictive engines extracted from mutual funds, works and translates to improved investment performance**. His conclusion:


Mathematical Foundation for Ensemble Machine Learning and Ensemble Portfolio Analysis

Eugene Pinsky
Department of Computer Science,
Metropolitan College,
Boston University Boston, MA 02215

> ***"We have provided a mathematical foundation for ensemble machine learning. The resulting ensemble portfolio has higher return than the corresponding stocks with weights from S&P 500."***

VI. Conclusion

Artificial intelligence is one of the most over-hyped terms in today's lexicon. But there is a power in this advanced technology, and not just from increasing the speed and breadth of data calculations. The real commercial benefit arises when AI allows a current *business model* to be re-engineered, allowing innovation to drive solutions not previously conceived. Solutions that are so improved that they become disruptive. ***Such as EAM***.

Consider:

- The subset of Machine Learning known as Ensemble Methods has been around for decades, and **routinely combines a series of stand-alone predictive engines into a stronger predictor**. The list of technical application stretches into the tens of thousands.
- Active management has suffered for decades against their mandate to outperform benchmarks. The **security selection decision-making is simply not sufficient to offset their costs**.
- Actively managed mutual funds can be easily viewed as predictive engines. The managers are trying to 'predict' which stocks will outperform. And research shows that managers' highest conviction stock picks reliably outperform (see Section V, Identifying Manager Selection in Security Selection).

It should therefore be viewed as a natural outcome to evolve from a **stand-alone portfolio as the dominant delivery format**, to a **multi-manager platform employing Ensemble Methods to create a superior offering**. It just required the insight, and means, to discover how to extract the predictive engine from a fund.

The EAM approach requires advanced technology, but its mechanics are surprisingly straight-forward:

1. **Utilize Ensemble Methods**, a proven technique for integrating a series of weak predictive engines into one with stronger predictive accuracy (Section III).
2. Use advanced technology (Hercules.ai) to **access current holdings and weights** of actively managed funds.
3. **Extract the predictive engine** embedded in all actively managed funds (Section V).
4. **Input the predictive engines into Ensemble Methods**, and allow the mechanics to do their job.

This study was designed to eliminate biases that would distort the outcome, and was then subjected to a rigorous independent academic review. One of the most important design features was the use of a random selection process for the Portfolio of Funds, and thus the EAM portfolios. **While better performing funds are preferred, this study proved that superior fund selection skill is not needed to properly power EAM portfolios**.

Sports analytics is an area where advanced technology fundamentally transformed an industry. The emergence of sports analytics and its impact on baseball was famously documented in the book *Moneyball*. There is a telling scene towards the end of the movie *Moneyball*[14] where John Henry, CEO of the Boston Red Sox, was recruiting Billy Beane, the GM of the Oakland Athletics, to become the next Red Sox General Manager:

> *"For forty one million, you built a playoff team. You lost [key players] and you won more games without them than you did with them. You won the exact same number of games that the Yankee's won, but the Yankees spent one point four million per win and you paid two hundred and sixty thousand.*
>
> *I know you've taken it in the teeth out there, but the first guy through the wall, he always gets bloody, always.* ***[But] anybody who's not tearing their team down right now, and rebuilding it using your model, they're dinosaurs****."*

In the world of professional baseball today, there are no teams that do not have a sports analytics department. The lesson has been learned, which begs the question: In the world of active investment management, which firms are going to evolve and embrace EAM, and which firms are going to be dinosaurs?

About the Authors

Vadim Fishman

Vadim is an entrepreneur and innovator, founder of several companies focused on novel technologies in Biology and Finance. Involved at the early stages of the genome revolution, Vadim designed key algorithms finding similarities in DNA and molecule structure.

Immediately prior to founding Turing Technology, Vadim was Managing Director and the Head of Asset Management Division at Incapital where he led efforts focusing Holdings Recognition technologies and Risk Sensitive Investment Strategies.

Turing is not Vadim's first entrepreneurial effort, as he also was the Co-Founder of Evolving Machines, LLC and Founder and CEO of IntelDM, Inc., a consulting firm providing mathematical and programming services for the financial services and biotech industries.

Vadim is fluent in multiple computer and web programming languages, software and database programs. He earned an MS in Technology from the Kharkiv Politechnical University in Kharkiv, Ukraine.

Robert Nestor

Rob has over 30 years of experience in asset management with functional business leadership roles across product development, enterprise commercialization, and distribution strategy. In recent years, he consulted with private equity and venture firms around early maturation and technology driven firms in the financial technology space, including the early-stage efforts of Qraft Technologies, an artificial intelligence (AI) driven asset manager. Prior to consulting efforts, Rob was President and Head of Direxion, a leading provider of ETFs and mutual funds with nearly $30B in assets under management (AUM). In this capacity, Rob led all aspects of the firm’s business including commercial strategy and business development.

Rob held a number of executive positions at Blackrock, including Managing Director and Head of iShares US Smart Beta ETFs, head of the iShares product strategy for Blackrock’s US Wealth Advisory (USWA) business, and Head of iShares Global Product Marketing and US Channel Marketing.

Before joining BlackRock, Mr. Nestor was at Vanguard, working in a variety of product and business development leadership roles in both the retail and institutional divisions. Key positions included running business, product, and marketing development for the Institutional Asset Management business, leading Vanguard's strategic business development in the area of retiree advice, product, and service development, leading Vanguard's Annuity & Insurance Services, and Global Head of Product Development, when Vanguard launched their first Exchange Traded Funds (ETFs) in the early 2000s.

Mr. Nestor is a CFA charterholder. He holds an M.B.A. from Drexel University in Finance - Investment Management and B.S. in Economics from the University of Delaware. He is also a member of the Financial Analysts of Philadelphia and the CFA Institute. Rob is also a founding and current Board member of the Philadelphia Chapter of Women in ETFs.

APPENDIX I: Independent Validation of Study and Methodology

The study was subjected to an independent academic review of methodology, design, and data integrity by Dr. David Goldsman, Coca-Cola Foundation Professor and Director of Master's Programs at the Georgia Institute of Technology's School of Industrial and Systems Engineering.

The Executive Summary of the report, as excerpted from the Validation Study, is provided below.

Turing Validation Study

Prof. David Goldsman

H. Milton Stewart School of Industrial and Systems Engineering
Georgia Institute of Technology
Atlanta, GA 30332-0205

"The goal of the project was to validate the methodology that Turing has used to arrive at their published results. In particular, we examined: (i) background methodology underlying Turing's work; (ii) statistical/randomness aspects of Turing's fund selection strategies involving the Enterprise Active Management (EAM) and Portfolio of Funds (POF) construction methodologies; and (iii) certain performance characteristics of the various portfolios, including estimated performance of strategies and comparison among strategies.

We found that the underlying methodology is sound, proper sampling/randomness protocols have been followed, EAM and POF construction has been carried out properly; and EAM and POF performance has been properly interpreted by Turing, including bias analysis and mitigation."
[emphasis added]

Professor Goldsman's Credentials and Academic Background:

Professor Goldsman is the Director of Master's Recruiting and Admissions and Coca-Cola Professor in the H. Milton Stewart School of Industrial and Systems Engineering at the Georgia Institute of Technology. He received his Ph.D. in 1984 from the School of Operations Research and Industrial Engineering at Cornell University. He also holds degrees from Syracuse University in Mathematics, Physics, and Computer and Information Sciences. He has been a Visiting Professor or Scientist at multiple universities domestically and abroad.

Professor Goldsman's research interests include simulation output analysis, statistical ranking and selection methods, and medical and humanitarian applications of operations research. He has published extensively, and has over 75 publications in such bellwether journals as Management Science, Operations Research, Operations Research Letters, IIE Transactions, and Sequential Analysis. He has also co-authored about 20 book chapters as well.

Professor Goldsman is an Associate Editor for Sequential Analysis and the Journal of Simulation. He was previously the Simulation Department Editor for IIE Transactions and an Associate Editor for Operations Research Letters. He was also the Program Chair for the 1995 Winter Simulation Conference (WSC) the IIE Board Representative to the WSC (2001–2009). Further, he has served in various elected positions for the INFORMS Simulation Society, including President.

Professor Goldsman and Christos Alexopoulos won the INFORMS Simulation Society's 2007 Outstanding Simulation Publication Award for their paper "To Batch or not to Batch?" which appeared in ACM TOMACS in 2004. In addition, he, Christos, Claudia Antonini, and Jim Wilson won the IIE Transactions 2010 Best Paper Prize in Operations Engineering and Analysis for their 2009 paper "Area Variance Estimators for Simulation Using Folded Standardized Time Series." Professor Goldsman received the INFORMS Simulation Society's Distinguished Service Award in 2002. He also received a Fulbright fellowship in 2006 to lecture at Boğaziçi and Sabancı Universities in Istanbul, Turkey. He is a Fellow of the Institute of Industrial Engineers and INFORMS.

APPENDIX II: Research Methodology

The key components to the White Paper analysis were:

- **Portfolios of Funds (POF)**: A randomly constructed group of 12 actively managed mutual funds, all within the same style and market capitalization grouping or asset class (e.g., Large Value).
- **EAM Portfolios**: A portfolio of 50 stocks representing the highest consensus level of conviction of the funds within each POF, obtained after deploying Ensemble Methods.
- **Benchmark**: The appropriate Russell total return index was used for each of the six asset classes.

The study design included a total of 60,000 randomly constructed Portfolios of Funds and 60,000 corresponding EAM Portfolios. The 60,000 portfolios were generated by building 10,000 within each of 6 asset classes: Large Value, Large Blend, Large Growth, Small Value, Small Blend, and Small Growth.

To be consistent with a core Ensemble Methods principle of independent underlying predictive engines, a filtering process was used in the construction of each POF which prevented more than one fund per fund family in any POF. This rule prevented more than one fund from the same fund family, and also prevented more than one share class for the same fund within any one POF. (NOTE: the fund selection process resulted, in rare occasions, in multiple share classes of the same fund being available in the fund selection pool.)

The pool of available funds that were used in the White Paper research was based on the following criteria:

- Funds all within one of the 6 asset classes mentioned above.
- Replicated data existed in the Turing Hercules.ai database with continuous daily returns within the database from 1/2016 through 12/2022.

The fund selection process resulted in 333 unique funds from 142 fund families. Total fund assets under management were more than $3 trillion, and reflected more than 60% of the total applicable industry assets.

For reference, funds were added into the Hercules.ai database based on a selection by one of Turing's **EAM clients** requesting a fund for either inclusion in a live EAM portfolio, or included in a backtest/research effort. Since the funds were added by Turing's clients for their EAM portfolios, there was a general bias towards funds that are deemed 'desirable' due to either performance results or brand. Some of the habitually weaker fund performers were likely excluded, but Turing did not influence the expansion of the database.

Each of the 60,000 Portfolios of Funds were built by applying a random generator to the full pool of available funds within each asset class. Statistical sampling was done after the entire POF data set was generated to ensure that sampling distribution was within a reasonable error range.

Use and Impact of Fees

The performance of the POFs were generated using the published return of each fund, on a net of fee basis, total return basis. The average annualized fee for the pool of funds was 0.87%[15]. Benchmarks were measured as publicly reported, without fees or transaction costs.

The performance of the EAM Portfolios were calculated in the same manner as the benchmark indexes with no fees or transaction costs added. As reference, a simulation calculation of the Large Blend asset class was conducted where the EAM Portfolios' returns were reduced by the maximum fee changed by Turing (25 basis points). **The success rate of EAM vs the POFs were at 71.5% without any added fees, and dropped very modestly to 69.7% with the maximum fee factored in to net relative performance**.

APPENDIX III: Limitations of the Data Analyzed

This research was conducted to provide a robust and realistic assessment of EAM Portfolios, with comparison to traditional actively managed mutual funds and standard industry benchmarks. However, all research efforts will have embedded biases and flaws embedded within the data and methodology. Key limitations of this data set included:

- All EAM portfolio data is based on hypothetical, simulated data. While the returns of each of the POFs and for each Benchmark are based upon live, published data, the EAM Portfolios were constructed on a hypothetical, historical basis.
- The time period for the analysis was limited. The 2016 to 2022 time period for the analysis included a broad range of investment markets (two bear markets, a strong and extended bull market, and a transition from growth style to value style). A longer window of evaluation would have provided more insight to the behavior of EAM portfolios in different market cycles.
- The majority of the underlying funds used in the construction of the POFs (and by extension the EAM portfolios) were obtained through a pre-existing database and were not selected with this analysis in mind. The fund list is believed to be a random sample, but unintentional biases are likely reflected in the final fund selection.

APPENDIX IV: Footnotes

[1] Morningstar Direct, Turing Technology.

[2] Morningstar Direct

[3,4] G. Seni and J. Elder, (2010), *Ensemble Methods in Data Mining.* Morgan and Claypool.

[5,6] S. Fortmann-Roe (2012), *Understanding the Bias-Variance Tradeoff. (scott.fortmann-roe.com)*

[7] G. Seni and J. Elder, (2010), *Ensemble Methods in Data Mining.* Morgan and Claypool.

[8,9] Turing Technology.

[10] Example: M. Cremers, (2017), “Active Share and the Three Pillars of Active Management: Skill, Conviction, and Opportunity”. Financial Analysts Journal.

[11] R. Cohen, C. Polk, B. Silli (2005), “Best Ideas,” SSRN-id1364827.

[12] A. Panchekha (2019), “The Active Manager Paradox: High Conviction Overweight Positions.” CFA Institute.

[13] E. Pinsky (2018), “Mathematical Foundation for Ensemble Machine Learning and Ensemble Portfolio Analysis,” Department of Computer Science, Metropolitan College, Boston University.

[14] Moneyball (2011), Directed by B. Miller, performances by B. Pitt, A. Howard. Sony Pictures Entertainment.

[15] Morningstar Direct, Turing Technology.