# ENSEMBLE ACTIVE MANAGEMENT

## THE NEXT EVOLUTION IN INVESTMENT MANAGEMENT

SEPTEMBER 2018

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# I. Executive Summary

This White Paper questions the superiority of the traditional Active Management paradigm. Do stand-alone, 'single-expert' investment managers or management teams, with well-defined yet rigidly entrenched philosophies and methodologies, deliver optimal results? The conclusion, derived from a database reflecting 30,000 test portfolios and 165 million data points, was that they do <u>not</u>.

> ***A new approach to investment management, referred to as "Ensemble Active Management" and representing the intersection of Artificial Intelligence and traditional Active Management, was proven the superior option.***

Some of the most compelling data supporting this conclusion can be seen in **Table 1** below. It shows the summary results of rolling 1-year and 3-year time periods comparing Ensemble Active Management Portfolios ("**EAM Portfolios**") to traditional Actively Managed funds (shown as "Fund Clusters"), and to the S&P 500. The analysis covered the period July 2007 to December 2017. In this analysis, the EAM Portfolios were adjusted to reflect a simulated net of fee returns (see *Section VI. Data Analysis and Implications* for details).

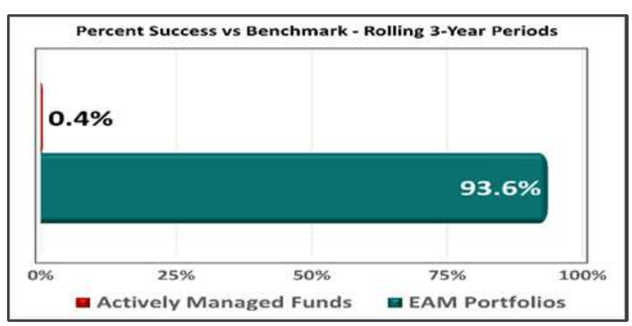
**Table 1. Probability of Outperformance and Annual Excess Relative Returns**

| Rolling 1-Year Periods | % of Time Outperformed | Annualized Excess Return | Rolling 3-Year Periods | % of Time Outperformed | Annualized Excess Return |
|---|---|---|---|---|---|
| EAM Portfolios vs S&P 500 Index | 72.3% | 3.4% (340 bp) | EAM Portfolios vs S&P 500 Index | 93.6% | 3.80% (380 bp) |
| EAM Portfolios vs Corresponding Fund Clusters | 82.3% | 3.3% (330 bp) | EAM Portfolios vs Corresponding Fund Clusters | 94.9% | 3.6% (360 bp) |

Key conclusions to be drawn from **Table 1** include:

- EAM Portfolios ***outperformed the S&P 500 72% of the time***, over rolling 1-year periods, with an average annual ***<u>excess</u> return of* 3.4% *(340 basis points)***;
- EAM Portfolios **achieved a *94% success rate versus the S&P 500*** for rolling 3-year periods, with an average annual ***<u>excess</u> return of* 3.8% (380 basis points);**
- EAM Portfolios ***outperformed traditional Active Management 82% of the time*** over rolling 1-year periods, and ***95% of the time*** for rolling 3-year periods.

For comparison, the fund rating firm Morningstar provides data allowing direct comparison of actively managed mutual funds vs their corresponding index funds, by investment category. For rolling 3-year periods (January 2008 to December 2017) the average Large Cap active fund outperformed the average Large Cap passive fund ***only one time out of 255 rolling periods, or 0.4% of the time*** (see bar chart to the right). On average, actively managed funds ***underperformed by -1.6% (-160 basis points) per annum***[1].




This data would compare to ***EAM Portfolios' 93.6% success rate vs the S&P 500*** (right-hand side, top row of **Table 1)**.

**SUMMARY BACKGROUND:**

There is no question that stand-alone managers or management teams have been the *de facto* paradigm for delivering Active Management for at least half a century. Yet, there is now a decade's worth of empirical evidence showing that traditional Active Managers have failed to reliably deliver on their mandate of outperforming the market after fees (see prior page, and *Section III, Traditional Active Managers' Glass Ceiling*).

This White Paper tests the viability of a new approach to Active Management, **Ensemble Active Management**, which is the result of traditional Active Management being 're-imagined' through the insights of technologists.

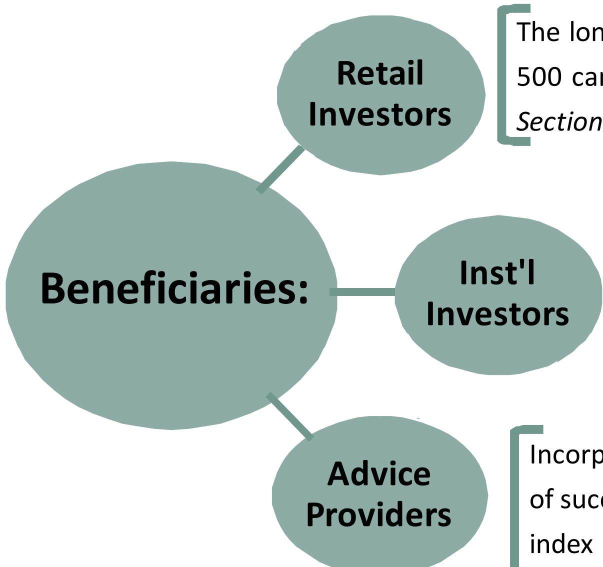
> ***Ensemble Active Management is built upon proven Artificial Intelligence techniques and technologies (primarily "Ensemble Methods") that have been successfully used within other industries for decades, and deploys a multi-expert approach, vs the single-expert paradigm of traditional Active Management.***

Ensemble Methods emerged several decades ago as a solution to improving the accuracy of predictive algorithms that had reached a point of diminishing improvement (i.e., hit a 'glass ceiling'). The breakthrough was the realization that if you could not improve a single, predictive algorithm beyond a certain threshold, you could improve results by **linking multiple, independent predictive algorithms and look for consensus or near-consensus agreement between them.** Ensemble Methods generate 'multi-expert' predictive systems, which have been proven to be superior to stand-alone 'single-expert' predictors. In their groundbreaking book *Ensemble Methods in Data Mining*[2]*,* Giovanni Seni and John Elder defined Ensemble Methods as:

> ***"the most influential development in . . . [Artificial Intelligence] in the past decade. They combine multiple [predictive] models into one [that is] usually more accurate than the best of its components."***

Technology firms have been successfully using Ensemble Methods to improve predictive accuracy in applications as varied as self-driving cars, weather forecasting, computer security, medicine, and even wine selection[3, 4, 5, 6, 7].

The broader implications of Ensemble Active Management can be profound. If it proves true that investors can reliably achieve returns exceeding that of the S&P 500, then the beneficiaries would include:




The long-term compounding of returns greater than that of the S&P 500 can potentially double **Retail Investors'** retirement savings (see *Section VII, Conclusion* for more details).

For **Institutional Investors**, higher returns would increase funding levels vs long-term obligations (e.g., retiree benefits), or provide improved funding for charitable/educational commitments.

Incorporating an active investment solution, with a higher probability of success vs index funds, would differentiate **Advice Providers** from index powerhouses such as Vanguard, re-invigorating their value propositions while also helping to justify their fees.

# II. Introduction

Artificial Intelligence ("AI"), has been on an impressive *tour de force* the last many years, seemingly revolutionizing one industry after another. Continued advances in computer processing capabilities, coupled with increasingly comprehensive databases (i.e., Big Data) have unleashed AI to disrupt and transform industries as diverse as health care, communications, manufacturing, and automotive[8, 9].


One of the most important advances supporting AI's impact has been the improvement in predictive algorithms and engines, resulting in increasingly impressive breakthroughs. From predicting landfall of a hurricane, to Netflix's recommendation engine, to facial recognition, the tech industry has ceaselessly improved the accuracy and benefits of its predictive algorithms and engines.

A critical insight that the tech world recognized decades ago was that virtually all predictive algorithms reach a point of diminishing returns. Each stand-alone predictive engine **eventually encounters a 'glass ceiling,' limiting improvements in accuracy** (see *Section IV. Ensemble Methods - Breaking Through the Glass Ceiling*).

But technology companies did not accept this limitation, and eventually discovered a powerful approach that enabled further improvements in predictive accuracy.

***They realized that if you could not improve a single predictive algorithm beyond a certain threshold, you could improve results by linking multiple, independent predictive algorithms and looking for consensus or near-consensus agreement between them. This approach effectively became the tech world's version of 'expert-based crowdsourcing'.***

The results were profound. By linking together multiple independent predictive algorithms, data scientists were able to break through the theoretical glass ceilings and target ever higher levels of predictive accuracy. This approach became known as **Ensemble Methods** and, over the ensuing decades, exotic sounding techniques such as Bagging, Boosting, Stacking, and Random Forests emerged to drive Ensemble Methods to ever greater heights.

***Surprisingly, one of the few sectors that has not seen broad-based application of Ensemble Methods is the mainstream investment management industry.***

Ensemble Methods are intended to be applied to predictive algorithms or engines. And at their core, actively managed mutual funds can be thought of as a predictive engine designed to identify securities that are likely to outperform the market.

And yet, it appears that the predictive engines driving Active Management have been, on average, subpar for an extended time (see *Section III, Traditional Active Manager's Glass Ceiling* for detail). There is now a decade's worth of empirical evidence showing that Active Managers have failed to deliver on their mandate to outperform the market after fees[1]. It appears that the proverbial 'glass ceiling' has taken up permanent residence within the world of Active Management, and, as demonstrated by the **trillion dollar shift in net flows** from active to passive managers over the past decade (see **Figure 2**), investors have recognized this reality.

This long-standing and growing concern regarding traditional Active Management's ability to deliver on its value proposition served as a powerful prompt, and applying Ensemble Methods to actively managed mutual funds (and thus creating "**Ensemble Active Management**") became the solution. The inspiration that led to creation of Ensemble Active Management was based on the following insights:

- ***In the eyes of a technologist, Actively Managed funds are simply single-expert predictive engines, designed to identify stocks that will outperform the market;***
- ***Ensemble Methods have been used by the technology industry for decades to improve the predictive success of single-expert predictive algorithms or engines;***
- ***THEREFORE, applying time-tested Ensemble Methods to the high conviction stock selections of actively managed mutual funds should result in superior predictive outcomes.***

Proving the efficacy of Ensemble Active Management became the hypothesis that this White Paper was designed to validate. As detailed in *Appendix I, Methodology*, a **scaled database was built to test this hypothesis, generating more than 165 million data points.** The results were persistent and striking (see *Section VI. Data Analysis and Implications* for complete details*)*.

***To those closest to the origin of Ensemble Active Management, the most striking question has <u>not</u> been "Why does Ensemble Active Management work," but rather "Why did it take so long for Ensemble Active Management to be discovered?"***

<u>HISTORICAL PERSPECTIVE</u>**:** In December 1975, Jack Bogle and The Vanguard Group filed for the first-ever index mutual fund and permanently changed the face of investment management. Their creation ushered in a new category of investment management: passive investing. Ever since, the investing world was defined by Active and Passive Management – two parallel and competing *philosophies* for building investment portfolios.

If Ensemble Active Management can be proven to work in live settings commensurate with this White Paper's data, then over time we will be referring to three philosophies of investment management: Traditional Active Management, Passive Management, and Ensemble Active Management.

# III. Traditional Active Managers' Glass Ceiling

The most fundamental distinction between Active Management and Passive Management lies in their respective objectives. Active Management has a remarkably clear and precise objective: outperform 'the market' after fees. Passive Management's stated goal is to deliver performance equal to 'the market', net of minimal fees.

## Testing Traditional Active Managers' Success Versus their Mandate

Unfortunately, for the past decade, the majority of Active Portfolios have failed to reliably and repeatedly outperform their benchmarks. One useful metric for evaluating reliability of performance is using rolling 1-year or 3-year periods. While a random performance spike for a month or two can distort 1-year or 3-year cumulative return numbers, looking at rolling time periods over longer windows mitigates the influence of outliers.

***Successful actively managed funds should be able to outperform their benchmark over rolling time periods the majority of the time (i.e., more than 50% of the time periods).***

The mutual fund ratings firm Morningstar provides data that allows a direct comparison between the average actively managed fund within an investment category (e.g., Large Cap Blend US equity) and the corresponding average index fund. This data enables a clean assessment of which approach/philosophy (Active Management or Passive Management) was the superior option for any historical time period. For example, the Morningstar category of Large Cap Blend has 109 discrete rolling 1-year periods from January 2008 through December 2017. Of the 109 periods, the average Active Manager outperformed the average index fund just 15 times, for a cumulative success ratio (or probability of success) of 13.8% (see **Figure 1**, left side, top row, center)[1].

The data in **Figure 1** builds upon the Large Cap Blend example above, and shows the results for all 9 primary US equity investment categories based upon rolling 1-year and 3-year periods over the past decade (Jan. 2008 – Dec. 2017), sorted by style and market capitalization. "AVG" refers to the average for each capitalization range.

**Figure 1: Percent Outperformance of Actively Managed Mutual Funds vs Index Funds (1/2008 – 12/2107)[1]**

**Rolling 1-Year Periods**

| | INVESTMENT STYLE | | | |
|---|---|---|---|---|
| | Value | Blend | Growth | AVG |
| Large Cap | 23% | 14% | 11% | 15.9% |
| Mid Cap | 29% | 8% | 26% | 21.1% |
| Small Cap | 39% | 18% | 33% | 29.9% |

**Rolling 3-Year Periods**

| | INVESTMENT STYLE | | | |
|---|---|---|---|---|
| | Value | Blend | Growth | AVG |
| Large Cap | 1% | 0% | 0% | 0.4% |
| Mid Cap | 2% | 0% | 2% | 1.6% |
| Small Cap | 29% | 8% | 4% | 13.7% |

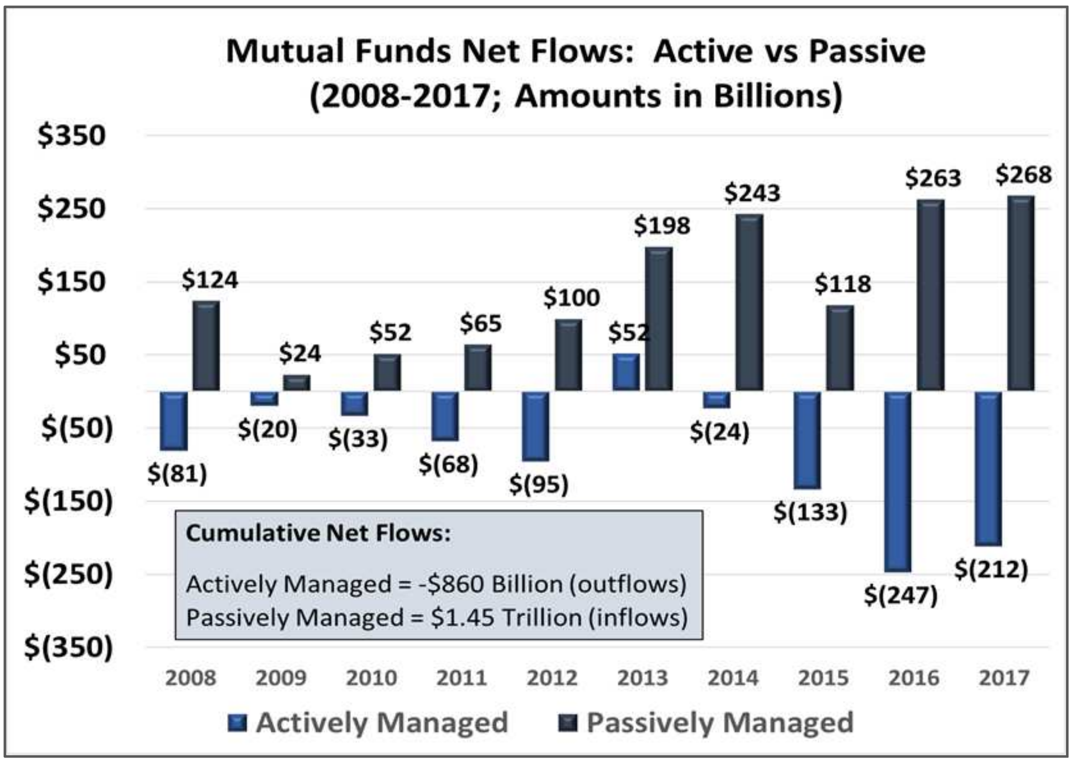
As can be seen, for rolling 1-year periods Active Managers were not able to breach the desired 50% percent success threshold in any of the traditional categories for US equities. In fact, the best results were from Small Cap Value with a 39% success rate. To be clear, this also means that ***the best results reflected a 61% failure rate***.

The data for rolling 3-year periods was even worse. The average Large Cap active funds (value, blend and growth) were only able to outperform 1 time in 255 rolling time periods, for an average success rate of an ***abysmal 0.4%.***

## Implications for Net Flows Between Active and Passive Managers

The marketplace has clearly taken notice. As an independent validation of the past decade's Active vs Passive performance results, and shown in **Figure 2**, net *outflows from* actively managed US equity mutual funds over the past decade have totaled more than $-860 billion, while net *inflows into* passively managed US equity mutual funds and exchange traded funds for the same time period have totaled nearly $1.5 trillion[1].

**Figure 2: Annual Net Flows for Active and Passive Funds[1]**



# IV. Ensemble Methods – Breaking Through the Glass Ceiling

The idea of seeking a second opinion (or third, or fourth) in matters of importance is second nature to most people. And for good reason. Consider a medical patient trying to decide between different treatment options. Surgery, drug therapy, homeotherapy? And then assume that this patient went to 5 medical experts and asked for their diagnosis and recommended treatment. If all 5 doctors provided the exact same diagnosis and recommended treatment, is there any doubt what that patient's course of action would be? Of course not. In virtually all cases, this type of *multiple-expert system* is better than a *single-expert system*, regarding both expected outcome and confidence in that outcome.

> ***Ensemble Methods is 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*[2], Seni and Elder defined Ensemble Methods as:

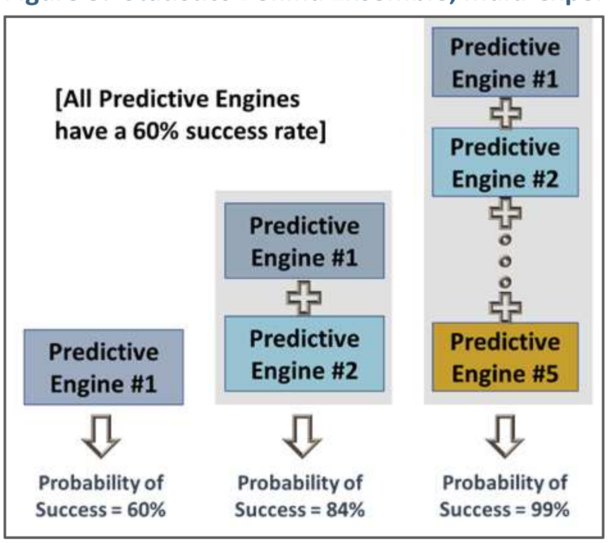
> ***"the most influential development in Data Mining and Machine Learning in the past decade. They combine multiple [predictive] models into one [that is] usually more accurate than the best of its components."***

The concepts behind Ensemble Methods date back to the late 1970's[10], and are considered a foundational approach for most AI and Machine Learning applications. Ensemble Methods are taught at virtually every university that has a Computer Science department, and have been successfully used in applications as varied as facial recognition, self-driving cars, weather prediction, computer security, medicine, and even wine selection[11].

### Why Do Ensemble Methods Work – Part A: Statistics

The science of statistics provides a clear explanation of how combining multiple predictive algorithms translates to improved outcomes. Just like the odds of flipping a coin and having heads appear twice in row is 25% [50% odds per flip, occurring twice in a row: 0.5 x 0.5 = 0.25], statistics can explain the expected improvements in predictive outcomes from Ensemble systems. Assume someone was attempting to predict a binary outcome (e.g., whether a plane would land at O'Hare airport on time). In this hypothetical, they had built several 'single-expert' algorithms, each of which were unique with independent errors[12], and in this example each predictor hit a glass ceiling at precisely a 60% success rate. Fortunately, a multi-expert system, achieving consensus agreement among partially flawed predictive engines, can still deliver high predictive results.

**Figure 3. Statistics Behind Ensemble, multi-expert systems**




As can be seen visually in **Figure 3**, the probability of an accurate prediction increases rapidly when the predictors agree (Note: this example assumes that the predictive algorithms are truly independent from one another). For example:

- If two predictors agree, the probability of success ***increases from 60% to 84%.***
- If five agree, the probability of success ***increases from 60% to 99%***.

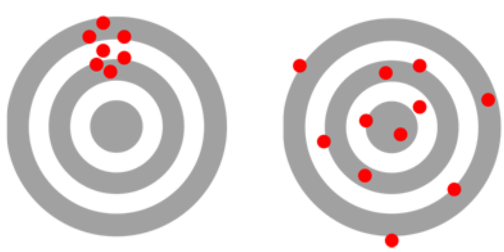
Obviously, multiple predictors rarely reach consensus agreement. But statistics can still shed light into how predictive success is improved through Ensemble Methods, even when consensus is not reached.

Building on the O'Hare example, this time an Ensemble of 21 independent and unique predictive algorithms were assembled to predict on-time landings, and each still had the same 60% success rate. In this case, they used a simple majority vote of the 21 algorithms to predict the outcome. Therefore, in order for this Ensemble prediction to be wrong, 11 or more of the predictors need to be wrong. The probability of such an outcome is only 17.4%, creating ***a success rate of 82.6% -- even though the underlying predictors all have a 'glass ceiling' at 60%.***

## Why Do Ensemble Methods Work – Part B: The Bias – Variance Conflict

As practitioners of Machine Learning know, the two most common errors impacting a predictive algorithm are 'Bias' and 'Variance'[13]. 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 4, left side**). Variance refers to its level of accuracy. A 'High Variance' algorithm will deliver results that have low accuracy (**Figure 4, right side**).

**Figure 4. High Bias (left) and High Variance (right) in Decision-making**



Unfortunately, all predictive algorithms have both intentional Biases as well as unintentional ones. And at a certain threshold, efforts to reduce bias will ironically increase variance[13]. This is sometimes referred to as the *Bias – Variance Conflict,* and it is a key contributor to single-experts' glass ceilings. This is where creating a multi-expert system through Ensemble Methods' tools and techniques changes the dynamic. Without triggering a discussion of higher level mathematics, one of the more digestible concepts is 'bias diversification'. Ensemble Methods actively link together multiple independent predictors, each with its own set of intentional and unintentional biases. Embedded diversification will allow the multiple biases to offset and partially neutralize each other, creating a new solution with a smaller bias.

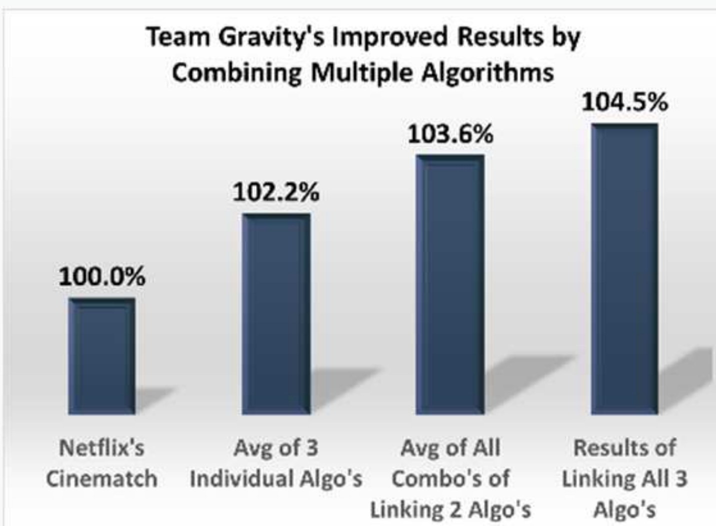
## CASE STUDY: The Netflix Challenge – Ensemble Methods in Practice

One of the most interesting examples of the power of Ensemble Methods is the $1 million Netflix Challenge[14, 15], where in 2006 Netflix offered $1,000,000 to the first team that could improve their proprietary *Cinematch* algorithm by 10%. It immediately became a siren's call for every Computer Science grad student, coding-geek, and even some of the biggest research firms in the country (such as AT&T Labs). Eventually, more than 40,000 entrees were submitted, from more than 5,000 teams covering 186 countries.


Initially, all of the entrants took a 'single-expert' approach, with some real signs of progress emerging quickly. The competition was launched October 2, 2006, and by October 15, 2006, three teams had already bested Netflix's Cinematch results by approximately 1%. By the end of 2006, dozens of teams were exceeding Cinematch, many approaching a 5% improvement. But then the proverbial 'glass ceiling' kicked in, and the rate of improvement slowed dramatically.

The first breakthrough came when individual teams began building 'multi-expert' Ensembles from their own predictors. For example, Team Gravity shared the details of their 2007 results obtained by creating Ensembles from three of their internal algorithms (**Figure 5**). They were able to achieve an average of a 2.2% improvement from their three single-expert algorithms, increased their results to an average of a 3.6% improvement by pairing the algorithms, and then achieved a 4.5% improvement over Cinematch when all three predictors were linked together.

**Figure 5. Team Gravity's Early Ensembles**




But Ensembles of three algorithms did not begin to describe the scale some of the teams were attempting. By the end of 2007 the best result came from team BellKor (from AT&T Labs), which used an *Ensemble of 107 internal algorithms* to achieve an improvement over Cinematch of 8.6%.

It took nearly three years, but eventually the 10% target threshold was reached. On September 18, 2009, Netflix announced the winning team, which was a 'super-Ensemble', created by linking together the efforts of three of the best independent teams: team BellKor, team BigChaos, and team Pragmatic Theory merged to create team **BellKor's Pragmatic Chaos**. Appropriately, the second place team was another super-Ensemble combination named **The Ensemble**.

# V. "Ensemble Active Management": Ensemble Methods plus Investment Management

As mentioned previously, an actively managed mutual fund can be described as a predictive engine designed to identify securities that are likely to outperform the market. This section explores the potential application for how these thousands of predictive engines (i.e., mutual funds) can fit within Ensemble models.

## Evaluating Mutual Funds Through the Lens of Ensemble Methods' Success Criteria

There are several criteria (see below) that usually provide a solid indicator for where Ensemble Methods will translate effectively to improved predictive outcomes. Based on those criteria, it can be argued that ***the actively managed fund industry is a near optimal environment for constructing high impact Ensemble Methods solutions.***

*NOTE: A mathematical validation of the beneficial impact of Ensemble Method techniques applied to mutual funds can be found in a recent academic paper by Professor Eugene Pinsky (Boston University), Mathematical Foundation for Ensemble Machine Learning and Ensemble Portfolio Analysis[20].*

Experience has shown that the ideal environment for Ensemble Methods occurs when the following exists[12]:

**Access to multiple, independently developed predictive algorithms or engines, with independent errors**.

- For the thousands of actively managed mutual funds in the U.S. alone, the standard industry paradigm is to use a 'single-expert' model, based on a stand-alone manager or team.
- Given the competitive nature of the industry, managers treat their methodology as a tightly guarded secret. By definition, the key predictive elements of each fund are designed to be unique.

**A broadly varied set of approaches/philosophies were used in the algorithm development**.

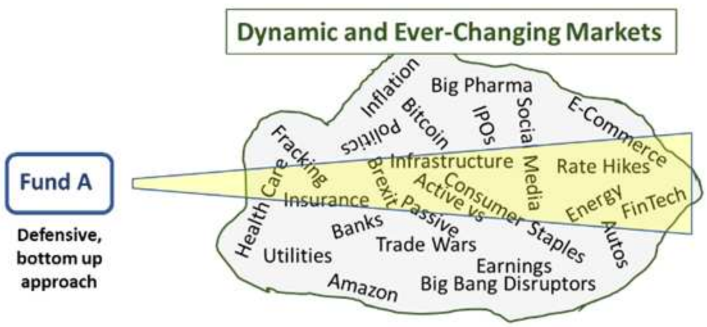
- The fund industry is highly competitive and over-saturated with products. Positive differentiation is difficult to achieve. Therefore, one of the established means of gaining differentiation is through sub-classifications of investment objective, and/or deploying unique approaches on style.
- Morningstar classifies more than three dozen U.S. investment categories, and within each there are unlimited variations in approach[1].

**A majority of the predictors achieved an accuracy level of at least 50%**.

- The financial incentives for successful fund managers are huge, creating full incentive for each fund manager to provide maximum effort, continually working to improve and refine their approach.
- While the data in *Section III, Traditional Active Managers' Glass Ceiling*, might suggest otherwise, there is substantive research indicating that managers' high conviction stock selections add value[16, 17].
  - For example, Cohen, Polk, and Silli: "Best Ideas" SSRN eLibrary. 2010. Where they state: ***"We find that the stocks that active managers display the most conviction towards ex-ante, outperforms the market, [ ] by approximately one to four percent per quarter".***

The final insight into why traditional mutual funds translate effectively to Ensemble Methods' techniques is based upon one of the quirks of the investment industry: virtually every actively managed mutual fund is established with a static and fixed investment approach (**Figure 6**.) Case in point, managers whose investment methodology reflects selecting the best growth companies do not randomly begin selecting companies with high dividend yield.

**Figure 6. Active Manager's Static Methodology**

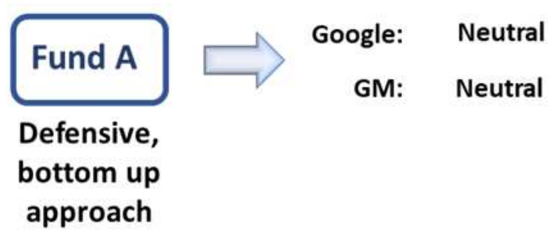



This industry paradigm would seem to be in conflict with the reality that the market is undergoing constant change: sector leadership rotates, bear market cycles give way to bull market rallies, while fear and greed switch places on a random and dynamic basis. And yet, this paradigm holds true nearly always. Perhaps ironically, this approach is another reason why Ensemble Methods are so effective a tool when applied to mutual funds.

## A Visual Representation of Deploying a Multi-Expert Ensemble System

In this section, we compare and contrast a hypothetical single-expert approach (represented by Fund A) to a multi-expert, Ensemble Methods-based approach (Funds A through H) in their evaluation of two potential holdings: Google (GOOG) and General Motors (GM).

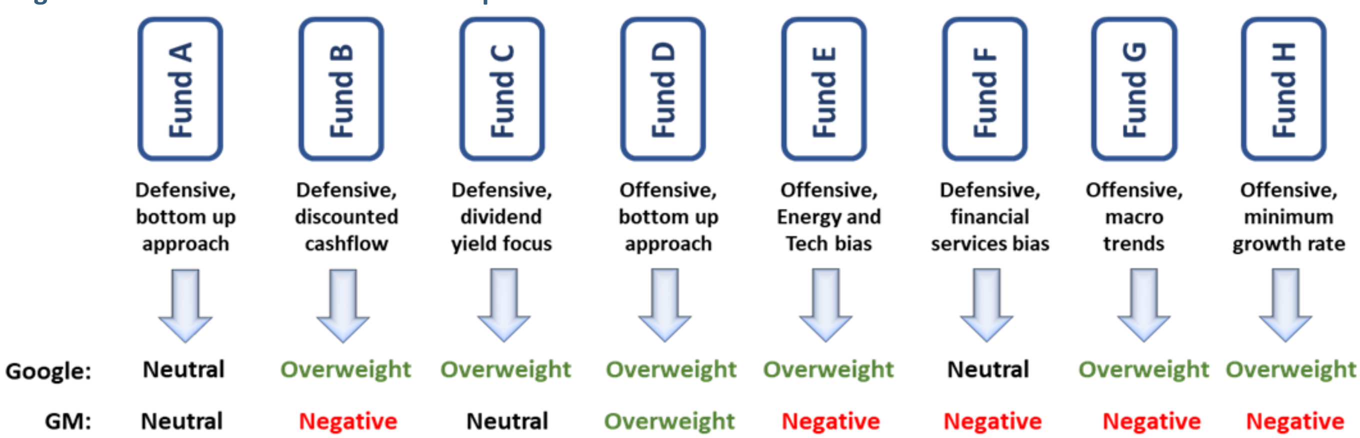
**Figure 7. Active Manager's Stock Selection**




As can be seen in **Figure 7**, in this example the Fund A manager gave both Google and GM a "Neutral" outlook, meaning he or she expects both stocks to perform in line with the S&P 500.

In **Figure 8**, the higher quantity, and quality, of information coming from the multi-expert Ensemble structure is apparent.

**Figure 8. Ensemble Methods' Multi-Expert Stock Selection**




Using a 'majority vote' Ensemble model, the resulting stock selection decisions are clearly apparent:

- 6 of the 8 Ensemble managers had Google rated as "Overweight," expecting it to outperform the S&P 500.
- 5 of the 8 Ensemble managers gave GM a "Negative" rating, expecting it to lag the market.
- ***The multi-expert, Ensemble model creates a clear, and high confidence, decision for Google and GM.***

# VI. Data Analysis and Implications

As fully detailed in *Appendix I, Methodology*, the data set supporting this White Paper was based upon 30,000 randomly generated clusters of 10 Large Cap funds each ("Fund Clusters"). For each Fund Cluster, there was a corresponding Ensemble Active Management Portfolio ("EAM Portfolio") constructed.

For clarity, the key vehicles evaluated as part of the White Paper analysis were:

- **Fund Clusters**: A randomly constructed group of 10 actively managed mutual funds.
- **EAM Portfolios**: A portfolio of 50 stocks representing the highest consensus over-weights of the funds within each Fund Cluster.
- **Benchmark**: the **S&P 500 Index**.

Rolling 1-year and 3-year periods were used to measure the probability of relative out- (or under-performance) between different constituents. Rolling time periods provide improved insights into reliability of returns.

**Given the potential industry-wide (disruptive) benefits of Ensemble Active Management, a scaled database was generated to ensure statistical accuracy, reflecting <u>165 million data points</u>.**

## Primary Performance Metrics Used within the Analysis

The performance analysis emphasized the following performance metrics:

**Percent Probability of Outperformance**

**RATIONALE:**

- For Investors, percent likelihood of outperformance is a ***statistical measure of 'odds-in-their-favor'***.
- The ***superior option will outperform over rolling time periods a majority of the time*** (i.e., more than 50% of the periods).
- When advisors, consultants or investors decide between different investment options, ***they will (rationally) choose the investment with the highest anticipated 'odds-in-their-favor' for future performance success***.

**Average Annual Excess Return**

**RATIONALE:**

- This metric addresses the question of ***scale of relative outperformance***.
- For an investor to justify shifting assets from one investment to another, they would expect:
    - The destination investment has a higher probability of future outperformance, and
    - The expected ***scale of outperformance is material, thus justifying the move.***

**Risk Metrics**

**RATIONALE:**

- Investments need to be evaluated in light of the associated risk. The risk metrics used herein capture:
    - ***Average risk*** (e.g., standard deviation), and
    - ***'Tail risk', or worst case events*** (e.g. max underperformance or relative performance in a bear market).

## Ensemble Active Management Portfolios -- Results

**KEY TAKEAWAYS:**

- EAM Portfolios ***outperformed the S&P 500*** for rolling 1-year periods ***72% of the time,*** with ***3.4% annual excess return.*** This compares to a ***16% success rate*** for actual active Large Cap funds vs index funds***.***
- EAM Portfolios ***outperformed 94% of the time*** over rolling 3-year periods. This compares to a ***0.4% success rate for actual, actively managed Large Cap funds vs index funds*** over rolling 3-year periods.
- EAM Portfolios ***generated a Sharpe Ratio (risk-adjusted-return) that was 20% greater than the S&P 500.***
- Anytime the S&P 500 lost -20% or more for a rolling 1-year period, the ***average EAM Portfolio outperformed.***
- Anytime the S&P 500 had any amount of loss for a rolling 3-year period, ***EAM Portfolios outperformed.***

## Probability or Outperformance and Annual Excess Returns – Rolling 1-Year Periods

**Figure 9. Rolling 1-Year Periods**

| Rolling 1-Year Periods | % of Time Outperformed | Annualized Excess Return |
|---|---|---|
| EAM Portfolios vs S&P 500 Index | 72.3% | 3.4% (340 bp) |
| EAM Portfolios vs Corresponding Fund Clusters | 82.3% | 3.3% (330 bp) |
| EAM Portfolios vs EITHER S&P 500 or Fund Clusters | 86.5% | n/a |

- EAM Portfolios ***outperformed the S&P 500 72.3% of the time, a nearly 3:1 advantage***.
- On average, the EAM Portfolios ***outperformed the S&P 500 by 340 basis points (3.4%) per annum, after fees***.
- EAM Portfolios had a higher probability of relative outperformance versus their corresponding Fund Cluster ***by more than a 4:1 ratio (82.3%), with annual excess return at 330 basis points (3.3%), after fees***.
- For any given time period, the EAM Portfolios had an ***86.5% probability of outperforming either the S&P 500*** (thus achieving the core objective of active management – exceeding the benchmark after fees), ***or at least outperforming the underlying Fund Cluster***, which would suggest that the investor would have been better off with EAM Portfolios versus a diversified portfolio of traditional Actively Managed funds.

## Probability or Outperformance and Annual Excess Returns – Rolling 3-Year Periods

**Figure 10. Rolling 3-Year Periods**

| Rolling 3-Year Periods | % of Time Outperformed | Annualized Excess Return |
|---|---|---|
| EAM Portfolios vs S&P 500 Index | 93.6% | 3.80% (380 bp) |
| EAM Portfolios vs Corresponding Fund Clusters | 94.9% | 3.6% (360 bp) |
| EAM Portfolios vs EITHER S&P 500 or Fund Clusters | 98.3% | n/a |

- EAM Portfolios ***achieved a 93.6% success ratio vs the S&P 500, with an average annual excess return of 380 basis points.***
- EAM Portfolios ***achieved a 94.9% probability of success vs the Fund Clusters, and a 98.3% probability versus either the S&P 500 or the Fund Clusters***.

**Figure 11. Percent Likelihood of Outperformance vs Benchmarks: EAM Portfolios and Avg Active Funds[1]**

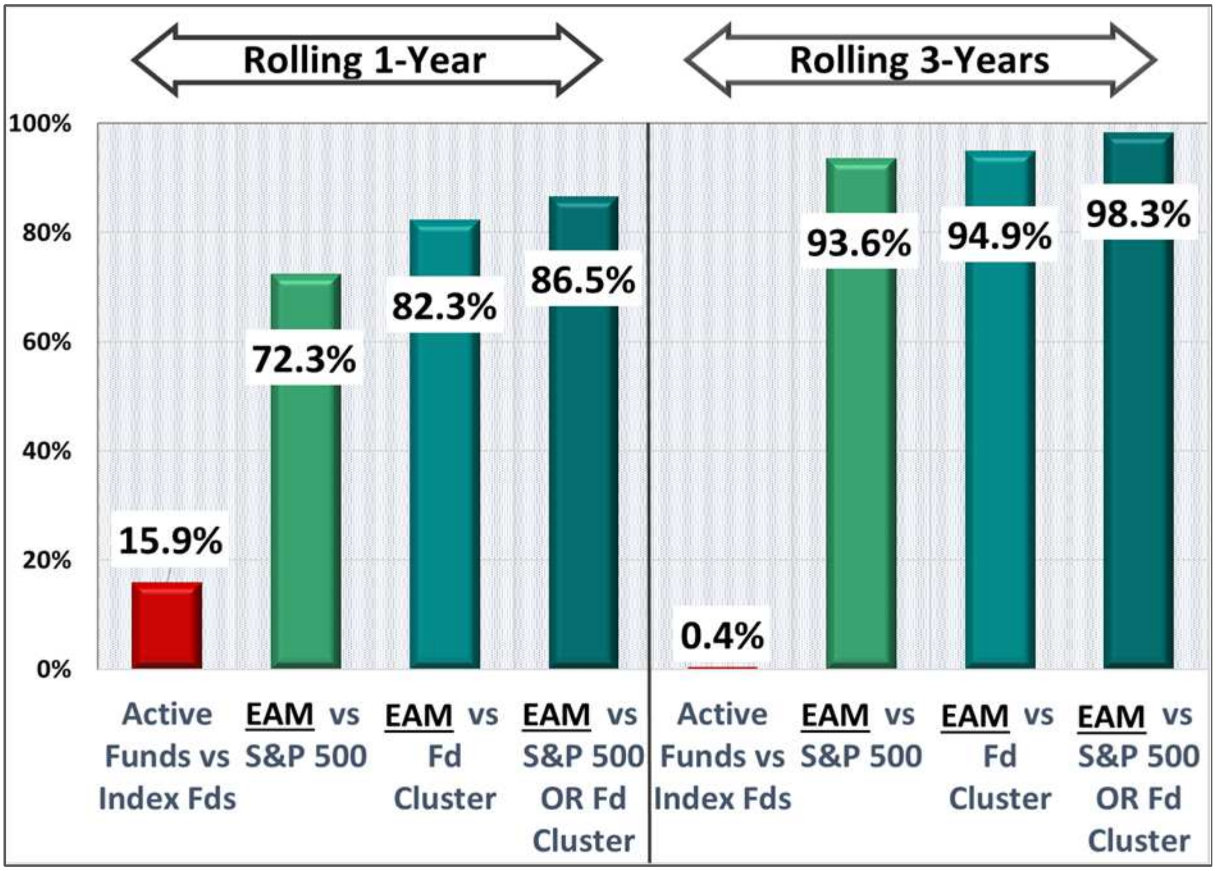



**Figure 11** integrates the White Paper's data regarding the probability of EAM Portfolios outperforming the S&P 500 and/or corresponding Fund Clusters (**Figures 9 and 10**), with the data from **Figure 1**, **Section III**, which showed the live results of Large Cap actively managed funds' success ratios vs corresponding index funds.

*While **Figure 11** does not provide a perfect comparison given slightly different methodologies and non-identical time periods (7/2007 – 12/2017 vs 1/2008 – 12/2017)*, there are still insights to be gained, particularly relating to Active Managers' stated objective of outperforming their benchmark after fees (i.e., a majority of rolling periods):

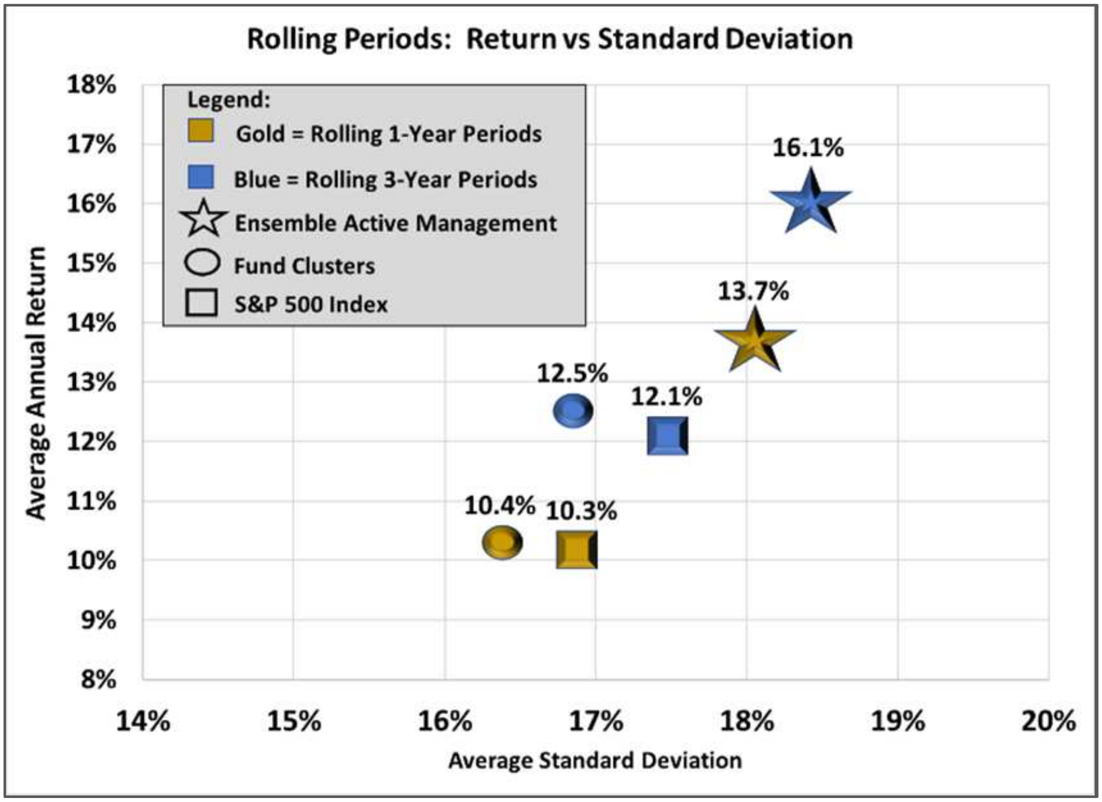
- The difference in ***probability of success for the live active funds (15.9% & 0.4%),*** as opposed to the ***EAM Portfolios (72.3% & 93.6%), is stark.***
- For rolling 3-year periods, ***EAM Portfolios' success rate vs ALL investment options exceeds 90%.***
- EAM Portfolios not only ***outperformed the S&P 500 a majority of the rolling periods, but exceeded a one standard deviation confidence level (>68%) for rolling 1-year periods, and is approaching a two standard deviation confidence level (>95%) for rolling 3-year periods.***

**Figure 12** (next page) evaluates the performance on a *risk-versus-return basis*. The gold symbols in **Figure 12** show results for rolling 1-year periods, and the blue symbols represent rolling 3-year data. In all cases, the return data (vertical axis) reflects the average annual returns for the rolling time periods. (Because the rolling 3-year periods act to smooth out the performance data, the S&P 500 average 3-year return is greater than the average 1-year return, even though the time period is identical.) The data labels reflect only return data (left-hand axis).

Summary data is as follows:

- EAM Portfolios ***increased return versus the S&P 500 by approximately one-third (33.4% for rolling 1-year periods, and 32.7% for rolling 3-year periods)***.
- EAM Portfolios had a ***slightly higher level of overall risk, with a 5% - 7% increase (7.0% and 5.4%, respectively***).

**Figure 12. Return vs Standard Deviation**




To determine if the benefit of increased performance outweighs the cost of the increased risk (i.e. are the risk-adjusted-returns superior), the two most common industry metrics are **Sharpe Ratio,** which measures risk and return versus a risk-free reference point, and **Information Ratio,** which measures risk and return versus the benchmark as a reference point. For both metrics, a higher value reflects a superior risk-adjusted-return.

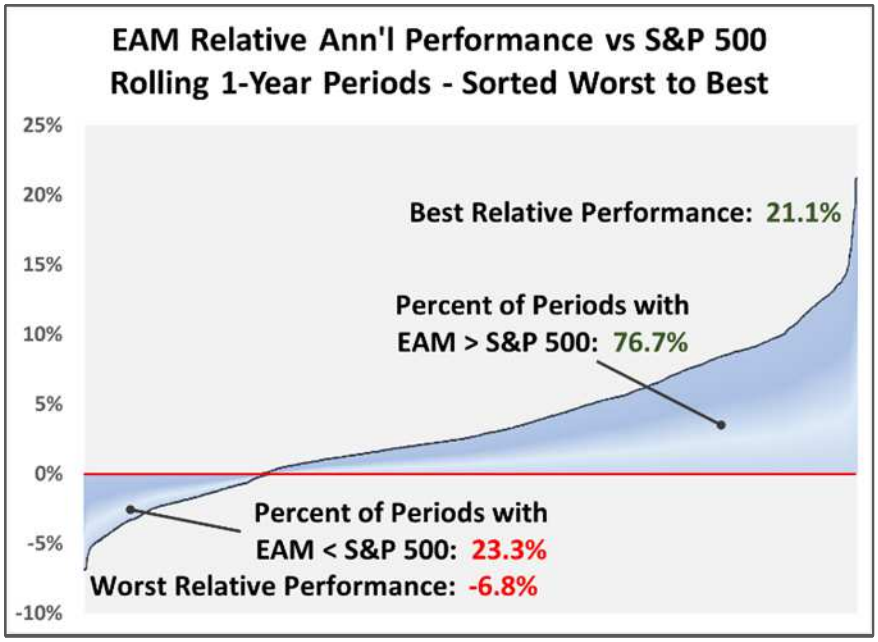
The risk-adjusted-return metrics (not charted) are as follows:

- Sharpe Ratio: EAM Portfolio's average Sharpe Ratio was ***1.04 for 1-year periods and 1.07 for 3-year periods, which improved upon the S&P 500's Sharpe Ratios of 0.89 and 0.88 by roughly 20%.***
- Information Ratio (IR): EAM Portfolio's average IR was ***0.87 for rolling 1-year periods and 0.99 for 3-year periods***. The S&P 500 had (by definition) IR's of 0.0 for both time windows[21].
    - By comparison, the Fund Clusters had IR's that were negative for both sets of rolling time periods.

**Figures 13 and 14** (following page) provide insight into *worst case, or tail, events*. These charts were constructed by taking the relative outperformance or underperformance of the EAM Portfolios (net of fees) vs the S&P 500 for each rolling time period, and sorting them from the worst underperforming to the best outperforming.

In **Figure 13**, anytime that the average EAM Portfolio *underperformed* the S&P 500 for a given 1-year period, it would appear as part of the light blue shaded area *below* the red line. Any time that the average EAM Portfolio *outperformed* the S&P 500 for a 1-year period, it is part of the blue shaded area *above* the red line.

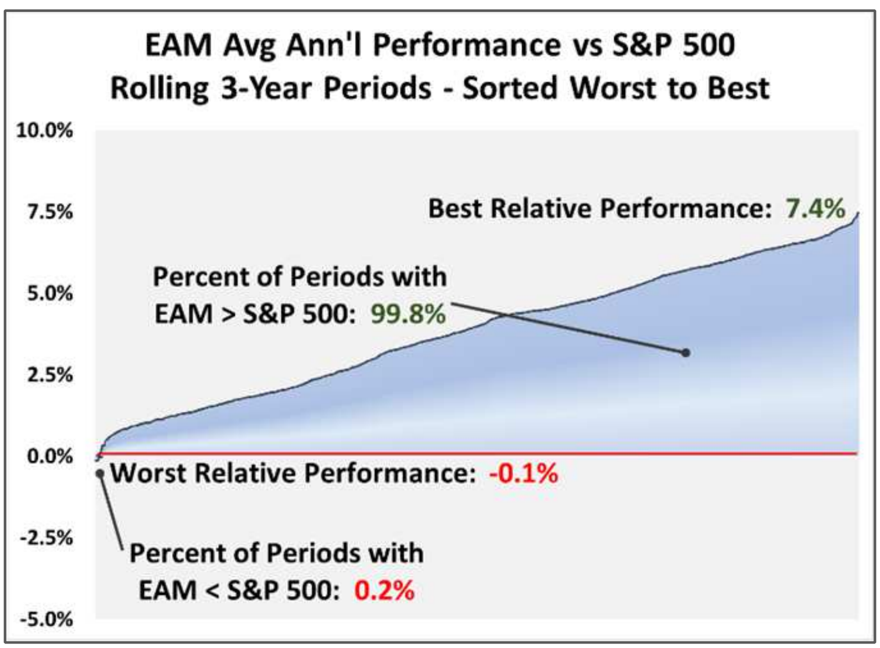
**Figure 13. Relative Returns – EAM vs S&P 500 (Rolling 1-year Periods, Sorted Worst to Best)**




- In the case of rolling 1-year periods, the single worst underperformance reflected an ***average shortfall of -6.8%*** (lower left-hand corner).
- The single ***best outperformance resulted in a 21.1% excess return*** (upper right-hand corner).
- When EAM Portfolios underperformed, the ***average underperformance was -2.3%.***
- When EAM Portfolios outperformed, the ***average outperformance was 5.2%.***
- This positive asymmetry in relative outcomes provides an additional, positive perspective on the risk and reward of deploying EAM Portfolios.

**Figure 14** shows the same data for rolling 3-year periods.

**Figure 14. Relative Returns – EAM vs S&P 500 (Rolling 3-year Periods, Sorted Worst to Best)**

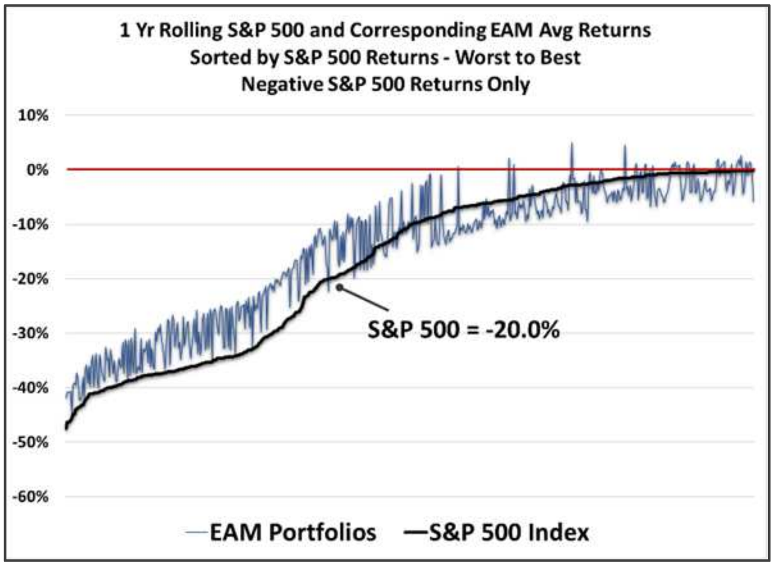



- In more than 99% of the time periods, the ***average EAM Portfolio exceeded the return of the S&P 500.***
- The single worst time period had the ***average EAM Portfolio lag the S&P 500 by only -0.1%.***
- When EAM Portfolios outperformed, the ***average outperformance was 3.8%.***
- This positive asymmetry seen with rolling 1-year periods is even more pronounced in rolling 3-year periods.

**Figures 15 and 16** continue the assessment of *worst case events*. **Figures 15 and 16** attempt to answer the question of when relative shortfalls are likely to occur. Obviously, if EAM Portfolios typically underperformed when the S&P 500 had already suffered a major loss, that would be adding insult to injury (fortunately, they did not).

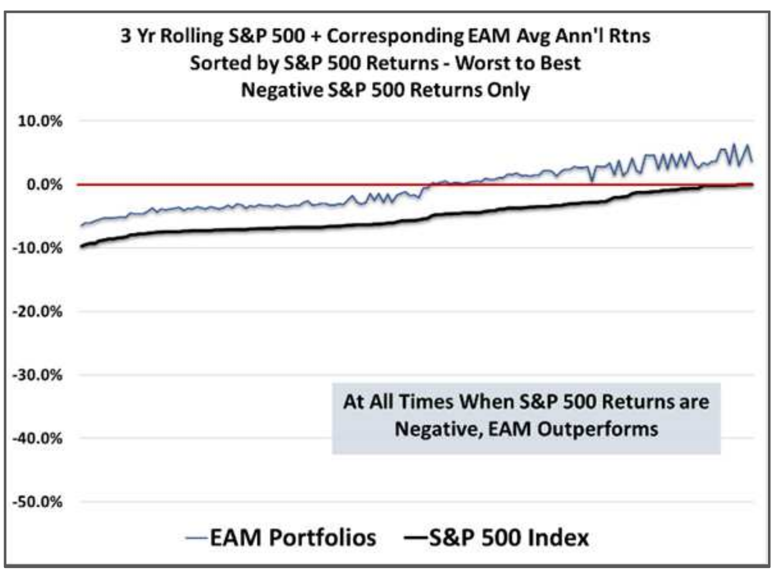
These charts were constructed by taking returns for each rolling 1-year time period and sorting them based on the performance of the S&P 500, worst to best*. In these charts, only periods of negative returns were shown.* The black line shows returns for the S&P 500, while the blue line shows the corresponding average EAM Portfolio returns for the same period.

### Figure 15. Relative Performance vs S&P 500 – All Periods Where the S&P 500 had Negative Returns (Rolling 1-Year Periods)




To clarify, **Figure 15** only shows the 1-year periods where the S&P 500 lost value, with returns for the S&P 500 ranging from -45.6% (for the 1-year period ending March 11, 2009) to a return of 0.0%. For the 1-year period ending March 11, 2009, the corresponding average EAM Portfolio lost -40.5%. While still a devastating loss, it was more than 500 basis points (5%) better than the return for the S&P 500 over the same time period.

### Figure 16. Relative Performance vs S&P 500 – All Periods Where the S&P 500 had Negative Returns (Rolling 3-Year Periods)

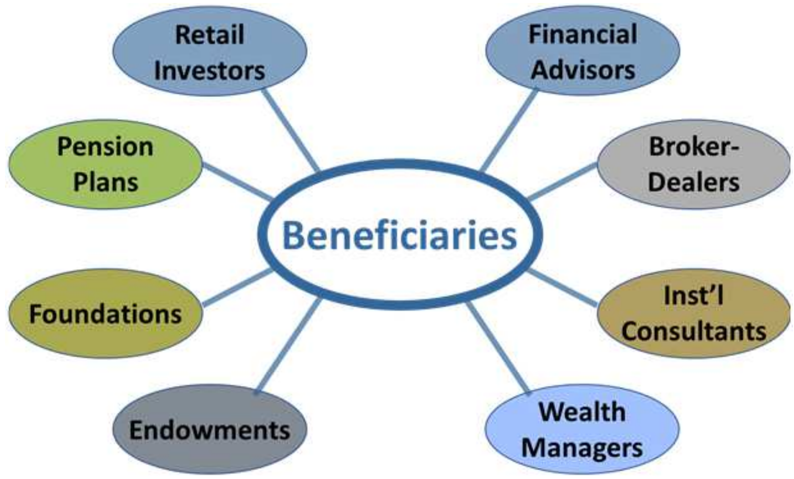



Summary conclusions for these two charts include:

- Any time that the ***S&P 500 had a 1-year loss of -20% or worse***, the corresponding ***EAM Portfolio outperformed the S&P 500***. (**Figure 15.**)
- Any time that the ***S&P 500 suffered a 3-year loss***, the corresponding ***EAM Portfolio outperformed***. **(Figure 16.)**

## VII. Conclusion – Throwing Down the Gauntlet

Relevance is oftentimes the missing ingredient to discussion documents. Innovation, impactful data, or simple novelty can capture attention. But change only follows if the insights have a positive – and tangible – impact on a deserving audience. If Ensemble Active Management is proven to deliver, in real market applications, results that even approximate the data presented in this White Paper, then the groups listed to the right are positioned to benefit in a substantial manner.




Some of the obvious beneficiaries would be the end investors whose long-term investment goals benefit from improved returns. But there are an additional class of beneficiaries who are in the business of providing advice, and they stand to benefit handsomely as their clients succeed.

The following is a more detailed look at a select few of these groups of beneficiaries:

### Retail Investors

- Based on conventional wisdom, the highest return a retail investor can expect to earn is the return of a low cost index fund. ***But what if through Ensemble Active Management investors can 'break through the glass ceiling' and earn more than the S&P 500 Index?***
- A simple math exercise can show the positive, long-term benefits of returns greater than the S&P 500:
  - Over the past 25 years the S&P 500 earned slightly more than 9.5%[18] per annum; $100,000 invested in January 1993 would have ***grown to $966,000 by December 2017***.
  - If an investor earned 13% a year (9.5% from the S&P 500 plus 3.5% per year (based on EAM Portfolios' rolling 3-year returns)), then the ***$100,000 would have grown to $2.1 million by December 2017***.

### Pension Plans, Endowments, Foundations

- Institutional investors manage portfolios with a mandate of funding critical activities such as future retirement or health care benefits, operating budgets for academic institutions, or charitable causes.
- Given the societal importance of these efforts, improved results would be imperative. Ensemble Active Management has a number of qualities that would appear to benefit these institutions, including:
  - Higher probabilities of outperforming traditional Active Management and/or indexes.
  - Investment portfolios that are liquid and transparent, are constructed entirely of securities residing within the benchmark, and do NOT use leverage or higher risk trading strategies.
  - An investment with materially higher Sharpe Ratios and Information Ratios.

**Financial Advisors & Institutional Consultants**

- For professionals whose business model includes recommending and building investment portfolios for clients, an increasingly difficult challenge has been achieving differentiation from the indexing juggernauts such as Vanguard, Schwab, and Blackrock.
- These advice-based professionals cannot compete with a firm such as Vanguard on price, therefore:
  - For decades one of the pillars supporting their value proposition has been building clients' investment portfolios that include actively managed investment products and funds, although . . .
  - As shown prior, the average active manager had a higher probability of failure than success.
- If mutual funds, SMAs, or ETFs based on EAM Portfolios become broadly available, and live results prove to be consistent with this White Paper's supporting data, ***then the business models and value propositions of these advice providers would be re-invigorated***.

Obviously, the dataset generated in support of this White Paper is hypothetical, theoretical, and based solely on historical data. *Appendix III, Limitations of the Data Evaluated*, discusses our assessment of the limitations of the data and methodology, and no doubt others will provide insight to even more important considerations. However:

- ***There is no denying that White Paper's results are significant, and have the potential to redefine the viability of active investment management.***
- ***There is no denying that the theory behind this Paper's hypothesis of applying time-tested Ensemble Methods to the high conviction stock selections of Active Managers indicates that Ensemble Active Management should work.***
- ***There is no denying that a scaled and robust database (165 million data points) was built to test the theory of Ensemble Active Management.***

Further, if **Ensemble Active Management** can truly break through the glass ceiling capping investment performance, then:

- ***There is also no denying that there are tens of thousands of institutional investors, hundreds of thousands of advice providers, and millions of retail and retirement investors whose lives would be tangibly improved.***

The baton is therefore being passed to the hands of the investment management industry. It is up to investment management firms, wealth managers, ETF manufacturers, and even large institutional investors and broker-dealer firms (see *Appendix II, Mechanisms to Deliver EAM Portfolios*) to bring to market investment solutions built upon Ensemble Methods' technologies and techniques, as well as investment solutions reflecting Ensemble Active Management principles and capabilities.

As products come to market, as they are tested by real market conditions, we will be able to observe if EAM Portfolios can live up to their potential.

# VIII. About the Authors

## The EAM Research Consortium

This White Paper and its supporting database was created through the efforts of the EAM Research Consortium. This is a group of technology professionals, data scientists, investment professionals, and academics who believe that Ensemble Active Management is a real and viable concept, and who have come together to advocate for its broader acceptance.

***To encourage broader industry engagement, the summary data generated in support of this White Paper will be made available for download to members of the EAM Research Consortium Group on LinkedIn. You can join the EAM Research Consortium Group on LinkedIn.***

## Contributing Editors

**Alexey Panchekha**

Alexey earned his MS (1988) and PhD (2000) from Kharkov Polytechnic University, before immigrating to the United States in the mid-1990's. From 1996 to 2016 he held a number of increasingly senior positions in the technology and financial services industries, including such firms as Broadvision Corp., Goldman Sachs, and Bloomberg. In 2016 he co-founded Turing Technology Advisors, a quantitative and Intellectual Property firm that uses proprietary technology to provide data and software solutions to a broad spectrum of potential clients.

**Robert S. Tull, Jr**

Bob has been a well-recognized expert in the ETF market since 1993, when he was one of the principals behind the development of WEBS -- the precursor to iShares ETFs. In the ensuing years he has consulting to issuers and governments on ETF infrastructure support, became a named inventor on multiple security patents involving exchange-traded products, and he has played a leading role in the design and development of over 400 exchange traded products in the U.S., Europe and Pacific Rim. Recently, Bob was presented the ETF 2018 Nate Most Lifetime Achievement Award.

Bob is one of the founders of ProcureAM, LLC, and prior to ProcureAM, Bob was the owner and primary consultant of Robert Tull & Company. Prior to launching Robert Tull & Company, he held senior level roles at such firms as Morgan Stanley, Deutsche Bank, where he was Managing Director and COO of Bankers Trust Global Custody, Benefit Payments and Master Trust business units, and the American Stock Exchange LLC (AMEX), where he was Vice President of New Product Development and Executive Director of AMEX ETF Services.

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Matthew is President of *Bell Family Interests LLC*, a private family office management and consulting firm. Mr. Bell is also an active investor in private companies through direct transactions, and is a Founding Member of the Alamo Angels Network. Prior to founding Bell Family Interests, he held a number of senior positions in the investment management industry, including Chief Investment Officer for *Cross Financial Services Corporation*, a Texas-based financial planning and investment management firm. Mr. Bell also formerly served as the President of the Financial Planning Association of San Antonio and South Texas chapter.

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# APPENDIX I: Methodology

The methodology was designed to assess if actively managed U.S. equity funds (i.e., single-expert predictors) can be successfully converted into a more accurate multi-expert predictive engine by applying Ensemble Methods technologies and techniques to the high conviction stock selections of a random selection of traditional Actively Managed mutual funds.

Ensemble Methods, by design, are intended to be applied to the predictive component of an algorithm or engine. In the case of mutual funds, the predictive element is the manager's high conviction security selections, which are also the securities with relative overweight positions versus the benchmark. To illustrate:

- As of August 16, 2018, Amazon (ticker = AMZN) represented 3.15% of the S&P 500 Index[19]. Hypothetical Manager A believed (predicted) that Amazon would outperform the market, and therefore allocated 5% of Fund A to Amazon. This means that Amazon had a 1.85% (185 basis points) overweight vs the S&P 500. *Therefore: Amazon would have been a high conviction security selection of Manager A.*

The key components to the White Paper analysis were:

- **Fund Clusters**: A randomly constructed group of 10 actively managed mutual funds.
- **EAM Portfolios**: A portfolio of 50 stocks representing the highest consensus over-weights of the funds within each Fund Cluster.
- **Benchmark**: the **S&P 500 Index** was used for the Large Cap funds.

The original design of the study was to build 400 Large Cap Fund Clusters and corresponding EAM Portfolios. However, based on the early data results which showed very strong EAM Portfolio outperformance, the study's scale was increased by nearly two orders of magnitude. The final study design included 30,000 Large Cap Fund Clusters and corresponding EAM Portfolios, with the data starting in July 2007.

- Relying primarily on rolling 1-year and 3-year periods with a daily step forward , the **database reflected 165 million data points** (i.e., the return of one Fund Cluster plus one EAM Portfolio plus the benchmark for one rolling time period equals three data points.

Details of the methodology include:

- The initial selection of the funds was based on a pre-existing database of 37 actively managed Large Cap US Equity funds. The funds within this database were NOT selected with this analysis in mind, but generally reflected high quality or top selling funds.
    - The database was unique in that it included estimated daily security holdings and weights for each fund. The holdings and weights were generated through an algorithm that used public holdings data (typically published monthly or quarterly, with a one-month lag) and interpolated the intermediary positions by relying upon the fund's published net asset value (NAV).
    - There was no ability to independently confirm that the holdings data was accurate, but sampling analysis gave confidence that it was a reasonable approximation of a fund's holdings.
    - The Large Cap funds had differing levels of historical data, so of the 30,000 Fund Clusters, only 10,000 had inception dates as of July 2007; 10,000 had inception dates starting April 2012, and the final 10,000 had inception dates starting April 2014.

- Each of the 30,000 Fund Clusters were built by applying a random generator to the full fund set, and thus selecting a random cluster of 10 funds each. Statistical sampling was done after the entire Fund Cluster data set was generated to ensure that sampling distribution was within a reasonable error range.
    - The database of 37 funds allowed a theoretical construction of several million Fund Clusters.
- Each of the 10 fund's resulting list of securities, with portfolio weights for each, were merged into a 'Preliminary Macro Portfolio' reflecting the combined results for all 10 funds.
    - The resulting weighting for each security in the Macro Portfolio reflected the average of that security's relative weights for all 10 funds.
- For each Fund Cluster's Macro Portfolio, the *portfolio weights* were converted into *relative weights*. The resulting portfolio was the 'Final Macro Portfolio'.
    - For example, as of June 30, 2017 Apple, Inc (APPL) represented 3.62% of the S&P 500 Index[22]. If the Apple weight within a Fund Cluster's Preliminary Macro Portfolio was 4.15%, then Apple would have had a weight of 0.53% (4.15% - 3.62%) in the Final Macro Portfolio.
    - If a fund's security holding was NOT included in the benchmark, that security was eliminated.
- The corresponding EAM Portfolio was built by taking the 50 stocks within each Final Macro Portfolio with the highest aggregated relative weights. The EAM Portfolio was then rescaled to 100% total weight to determine the final EAM Portfolio composition.
- The entire procedure was repeated (reconstructing securities and weights) every two weeks.

***NOTE: This methodology used the most straightforward Ensemble Methods construction approach available. More sophisticated or complicated methodologies were avoided to allow for cleanliness and transparency.***

## Use of Fees

The performance of the Fund Clusters was generated using the published return of each fund, on a net of fee basis. The average (across all years) Large Cap fund's annualized fees were 0.94%[1].

The performance of the S&P 500 Index reflected no added fees.

The performance of the EAM Portfolios were reduced to reflect the average annualized fee of the funds in the database, based on the funds' fees for that year. This approach **created a simulated net of fee calculation**. Thus, the performance of all EAM Portfolios were reduced on average (across all years) by 0.94% per annum.

# APPENDIX II: Mechanisms to Deliver EAM Portfolios

In addition to the Methodology utilized in support of this White Paper, there are several approaches that have been identified for creating Ensemble Active Management solutions. Some of the approaches will be appropriate for only certain investment institutions, while some of the approaches might enable new entrants into the investment industry. The suggested (non-exhaustive) list of approaches include:

- **<u>Large Active Fund Managers Applying Ensemble Methods to Existing Funds.</u>** The largest investment firms have multiple funds and investment strategies within key investment categories. They can construct an Ensemble Active Management solution by having an independent quantitative analyst take the list of fund holdings and weights for all of the portfolios on a periodic basis, and build a new, integrated, 'multi-expert' Ensemble portfolio.
- **<u>Pension Plans, Broker-Dealers and Large Wealth Managers Applying Ensemble Methods to Sub-Advisors' Holdings Data.</u>** A traditional approach for when a Pension Plan is allocating a portion of their portfolio to active managers would be to 1) split the targeted investment amount among a handful of managers, 2) send them the assets to manage, and 3) pay them for the portion that the manager controlled. An EAM alternative would be for the Pension Plan to pay the managers for *their list of holdings and weights*, apply Ensemble Methods to the combined list of securities from all of the active managers, and trade the resulting EAM Portfolio themselves.
- **<u>Boutique Managers Applying Ensemble Methods to a Consortium of Similar Managers.</u>** There are untold number of boutique managers, independent investors, and small wealth managers who might manage a stand-alone portfolio, but lack the breadth and depth of research resources of the larger firms and/or lack the distribution prowess required to successfully raise meaningful assets. However, some of these individuals and firms can connect and form a consortium, and use a third party quantitative analyst to apply Ensemble Methods to the individual sets of holdings and weights. They could then collectively market the resulting (and likely superior) EAM Portfolio, and then split any revenue generated by the Ensemble solution on a pro rata basis between the consortium members.

# APPENDIX III: Limitations of the Data Analyzed

While the data set was intended to provide a realistic assessment of EAM Portfolios as an alternative investment category to traditional Active Management and Passive Management, there are always 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 Fund Clusters 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 time period for the analysis dates back to July 2007, which includes one bear market and a strong and extended bull market. A longer window of evaluation would have provided more insight to the behavior of EAM Portfolios in different market cycles.
    - As mentioned previously, only 10,000 (out of 30,000) of the Fund Clusters had a start date of July 2007.
- The majority of the underlying funds used in the construction of the Fund Clusters (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

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# APPENDIX V:  Glossary of Key Terms

*NOTE:  Many of the following definitions were based upon information from Investopedia.*

**Active Management:** Active management consists of a individual manager or management team making buy and sell decisions based on research, conviction and other factors.  Active Management's objective is to exceed the performance of its benchmark after fees.

**Algorithm:** An algorithm is a sequence of rules for solving a problem or accomplishing a task.

**Artificial Intelligence:** Artificial intelligence (AI) is a term for simulated intelligence in machines. These machines are programmed to "think" like a human and mimic the way a person acts. The ideal characteristic of artificial intelligence is its ability to rationalize and take actions that have the best chance of achieving a specific goal, although the term can be applied to any machine that exhibits traits associated with a human mind, such as learning and solving problems.

**Asymmetry:** Asymmetry related to an investment refers to probabilities of outcomes where the potential for loss is tangibly different than the potential for gain (i.e., not symmetrical).  Positive asymmetry is where the potential (or realized) gains are tangibly greater than the potential (or realized) losses.

**Basis Point:** A basis point is a unit of measure used in finance to describe the percentage change in the value or rate of a financial instrument.  One basis point is equal to 1/100th of a percent.

**Bias:** Biases in humans are tendencies that affect our behavior and perspective, based on predetermined mental notions and beliefs.  Biases in algorithms occur when the underlying assumptions in the predictive algorithm are flawed.  A 'High Bias' predictor will generate results that are consistently off target.

**Big Data:** Big Data refers to an accumulation of data that is too large and complex for processing by traditional database management tools.

**Ensemble Active Management ("EAM"):** Ensemble Active Management is the result of traditional Active Management being 're-imagined' through the insights of technologists, and is the result of proven Artificial Intelligence techniques and technologies (primarily "Ensemble Methods") being applied to the high conviction stock selections of traditional Active Managers.  EAM deploys a multi-expert approach, vs the single-expert paradigm of traditional Active Management.

**Ensemble Methods:** Ensemble Methods is a time-tested component of Artificial Intelligence and Machine Learning, with its first use dating back to the 1970's.  Ensemble Methods use a variety of mathematical techniques to link together 'single-expert' predictive algorithms to generate a 'multi-expert' predictive systems, which under most circumstances have been proven to be superior to stand-alone 'single-expert' predictors.

**Fund Flows:** Fund flow is the net of all cash inflows and outflows in and out of various financial assets. Fund flow is usually measured on a monthly or quarterly basis; the performance of an asset or fund is not considered, only share redemptions, or outflows, and share purchases, or inflows.

**Information Ratio:** Information Ratio is a term used to measure risk-adjusted-return. It is calculated by determining the ratio of excess returns versus a benchmark relative to the volatility of those returns.

**Investment Methodology:** A system of broad rules that define the approach an investment manager will use to build their investment portfolio. Unlike an algorithm, a methodology is not a formula, but a set of practices.

**Investment Philosophy:** An investment philosophy is a set of beliefs and principles that guide an investor's decision-making process.

**Large Cap Blend:** Large Cap Blend is a type of investment category where the portfolio is comprised of large capitalization stocks, and a blend of growth and value stocks.

**Morningstar, Inc.:** Morningstar is a Chicago-based research and investment firm that offers various products and research insights in over 27 markets around the world.

**Overweight positions:** An overweight position refers to a security within an actively managed portfolio that has a greater portfolio weight than that security's weight within the portfolio's corresponding index or benchmark. A security with an overweight position would typically represent a high conviction stock selection on the part of the manager, and reflective of the manager's belief that the stock will outperform the broader market.

**Passive Management**: Passive management refers to index- and exchange-traded funds (ETFs) which have no active manager and typically lower fees. Passive Management's objective is to replicate the underlying index as closely as possible. Traditionally, Passive Management operates at very low fee levels.

**Predictive Algorithm:** A predictive algorithm is an algorithm that is used to predict the outcome of some type of activity or event.

**Predictor:** A predictor is another term referring to any predictive algorithm, engine, or system.

**S&P 500:** The Standard & Poors 500 is an index reflecting a basket of 500 stocks that are considered to be widely held. The S&P 500 index is weighted by market value, and its performance is thought to be representative of the stock market as a whole, and provides a broad snapshot of the overall U.S. equity market. The S&P 500 index was created in 1957.

**Sharpe Ratio:** Sharpe Ratio is a term used to measure risk-adjusted-return. It is calculated by determining the average return earned in excess of the risk-free rate, per unit of volatility or total risk.

**Style and Market Capitalization:** Style refers to the investment approach or objective that a fund manager uses. A value style is where the manager attempts to find stock that are cheaper than the average; a growth style is where a manager attempts to find stocks that are growing faster then the average. A blend style is one that combines elements of both value and growth.

**Variance:** Variance is the spread between numbers in a data set and their mean, and for an algorithm refers to its level of accuracy. A 'High Variance' algorithm will deliver results that have low accuracy.