Core Matters

Machine Learning and Tactical Asset Allocation – Part III: The Multi-Asset Class Case

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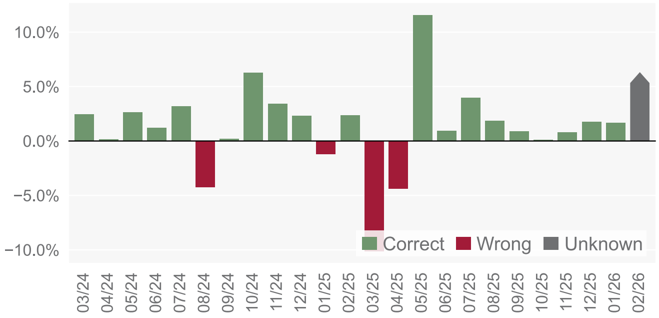
Our Core Matters series provides thematic research on macro, investment, and insurance topics

- kNN (**k** **N**earest **N**eighbours) is a machine learning classification algorithm. For our TAA use case this algorithm matches today's macro environment to its closest historical look-alikes and uses the market moves that followed those periods to derive forecasts.
- Two kNN models assessing the relative attractiveness of Equities vs Government Bonds are already embedded in our Research TAA process. Over the past two years, the US model achieved 83% accuracy (see chart), and the euro-area model 63%.

ML Signal Check for the US

Return Differential EQ vs GV*



Source: Datastream, GenAM

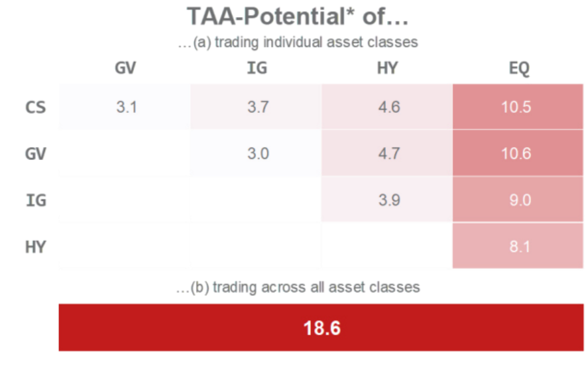
**Based on average mid-month data for the United States-Datastream Market Index (EQ) and ICE BofA US Treasury Index (GV)*

- By "trading" Equities against Government Bonds, these two models already target one of the most rewarding levers in classical TAA. Other binary classification tasks such as High Yield Credit vs Investment Grade Credit are also worth scrutiny. However, simply combining isolated pairwise comparisons lacks the ability to capture interactions across pairs adequately. In a multi-asset class universe comprising Equities (EQ), High Yield Credit (HY), Investment Grade Credit (IG), Government Bonds (GV), and Cash (CS), jointly evaluating all five asset classes would have lifted the TAA potential by more than 25% compared with just combining the two pairs EQ vs GV and HY vs IG.
- Extending the algorithm beyond a two-asset class framework requires overcoming additional methodological challenges. In the two-asset class case there is only one degree of freedom: classifying EQ as the outperformer automatically implies GV as the underperformer, and vice versa. In the five-asset class case, we must determine a joint ranking across all asset classes while (i) using a single, shared neighbourhood for each asset class and (ii) enforcing consistency of the forecasted ranks.
- Our five-asset class kNN model was trained and tested on monthly US macro data from the FRED-MD. In a true out-of-sample check covering 01/2022–10/2025, the signal-based TAA delivered +7.2 bps per month of added value, with a 75% success rate over the past two years.

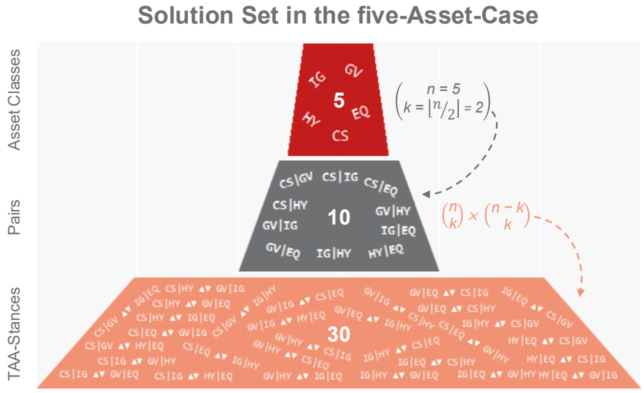
CONTENT

1. Motivation

With the beginning of 2024 we successfully integrated a Machine-Learning kNN model that forecasts the relative attractiveness of EQ vs GV for the US into the Research TAA process. It matches today's macro environment to its closest historical look-alikes and uses the market moves that followed those periods to derive forecasts via a majority vote, see Machine Learning and Tactical Asset Allocation (Part I). Over the past two years, this model achieved 83% accuracy (see chart on the frontpage), and a euro-area version introduced shortly afterwards achieved 63%. In this paper, we extend the binary approach to a multi-asset class case to enhance the scope of ML-backed TAA outperformance.



Source: Datastream, GenAM; monthly data from 08/92 to 09/25
*Median of monthly outperfomance in bps achievable under return maximisation with a constant TAA-range of ±4 pp



Source: GenAM

The upper left-hand chart shows all TAA potentials[1] in an asset class universe comprising EQ, HY, IG, GV, and CS[2]. Taking the correct active position just in EQ and GV

[1] The TAA potential is the maximum outperformance achievable by taking active positions in two (section (a) in the chart) or all five (section (b)) asset classes. Throughout this paper we assume these active positions to be always ±4 pp around benchmark as a realistic band in practice. Using different values would only scale up or down the results but would not change the conclusions. All data refers to the US. Monthly data means mid-month total return data. Mid-month is defined as the average of the 14th to 16th of each month.

[2] CS: ICE BofA 0-3 Month US Treasury Bill Index (MLTB03L); GV: ICE BofA US Treasury Index (MLTRSML); IG: ICE BofA US Corporate Index (MLCORML); HY: ICE BofA US High Yield Index (MLHMACL); EQ: US-DS Market (TOTMKUS); source: Datastream

(staying neutral everywhere else) would have generated a median monthly outperformance of 10.6 bps over the past 33 years. The same approach applied to HY vs IG would have added 3.9 bps per month. Thus, we would have ended up with 14.5 bps of monthly added value in total when simply combining the active positions of these two pairwise approaches.

Considering all five asset classes simultaneously when taking the active positions would have raised the median monthly outperformance to 18.6 bps, an increase of more than 25%. Deriving the active positions from pairwise comparisons between asset classes lacks the ability to capture interactions across pairs adequately[3]. By “trading” EQ against GV, our two implemented models already target one of the most rewarding levers in classical TAA. Models covering other pairs of asset classes (e.g. HY vs IG[4]) do have their own merits. Yet, exploiting the full TAA potential of a multi-asset class universe requires the simultaneous modelling of all asset classes.

2. Methodology & Implementation

A standard kNN always classifies just one observation, i.e. one asset class in our application. For our seminal pairwise model (EQ vs GV) this is fully sufficient as there are only two potential outcomes. Either the model prefers EQ over GV or GV over EQ. Thus, there is only one degree of freedom: classifying EQ as the outperformer automatically implies GV as the underperformer, and vice versa.

Extending the scope of the kNN algorithm beyond two asset classes introduces additional methodological challenges. In the five-asset class case we are facing 30 potential model outcomes (see right-hand chart on page 2). Thus, we must classify all asset classes simultaneously while

(i) using a single, shared neighbourhood for each asset class and

(ii) enforcing consistency of the forecasted ranks.

2.1 From Classification to Ranking

With just two potential outcomes in the two-asset class case, the model outcome is either right or wrong. There is nothing in between. Thus, accuracy – a standard measure in machine learning to assess the quality of the model and just the share of true model outcomes – is applicable[5].

In the five-asset class case this no longer holds as we are making a step from black & white to shades of grey. I.e. now, a particular model outcome can not only be (completely) right or (completely) wrong, but it can also be in part right or in part wrong, which makes the accuracy no longer applicable. Instead, we now use the added value of a model-determined TAA to train our model.

[3] Doing the comparisons pairwise means always overweighting one asset of the pair against the other. This approach will fail in case the optimal solution requires overweighting both assets of one pair against both assets of the other pair.
[4] Additional information on our models covering HY vs IG for the US and EA are available upon request.
[5] Although this is true, we trained our pairwise models on a criterion that basically weights the accuracy with the return differential (see our Core Matter: Machine Learning and Tactical Asset Allocation (Part I)). As return differentials between EQ and GV vary substantially over time and large potentials tend to be in rather favour of GV (i.e. when Equity markets “crash”).

Given a constant tactical allocation range (i.e. the absolute value of feasible over- and underweights for each asset class in pp, ΔTAA) the maximum added value can be directly calculated from the individual asset classes' returns ($r_{(i)}$) as follows[6]:

$$MaxOutperf = \left(\sum_{k=1}^{\lfloor n/2 \rfloor} r_{(k)} - \sum_{k=n-\lfloor n/2 \rfloor+1}^{n} r_{(k)}\right) \cdot \Delta TAA \quad \text{with } r_{(1)} > r_{(2)} > \cdots > r_{(n)}$$

Thus, the maximum added value equals the difference of sum of returns in the floor of n over two top performing asset classes (TOP performers) minus the sum of returns in the floor of n over two bottom performing asset classes (BOTTOM performers)[7] multiplied with the TAA range. I.e., for an optimal allocation it is sufficient to differentiate between these two groups of performers[8], as all TOP performers will be overweighted and all BOTTOM performers underweighted to the same amount. The individual position of an asset class within one of these groups is irrelevant. Thus, (a) from five asset classes we arrive at 10 possible pairs forming the groups of TOP and BOTTOM performers[9] and (b) from these 10 pairs we arrive in turn at 30 possible model outcomes or TAA stances[10] (see right-hand chart on page 2).

Neighbourhood				Asset Classes (True Return Ranking)				
	Date		Weight	CS	GV	IG	HY	EQ
(1)	Year 1	Month 1	35.2%	1	2	5	3	4
(2)	Year 1	Month 2	24.7%	3	1	5	4	2
(3)	Year 2	Month 3	22.4%	5	3	1	4	2
(4)	Year 3	Month 7	17.7%	1	3	2	5	4

Forecast Probabilities

STEP 1	CS	GV	IG	HY	EQ
TOP	52.9%	59.9%	40.1%	0.0%	47.1%
MID	24.7%	40.1%	0.0%	35.2%	0.0%
BOTTOM	22.4%	0.0%	59.9%	64.8%	52.9%
FORECAST$_{init}$	*TOP*	*TOP*	*BOTTOM*	*BOTTOM*	*BOTTOM*

Source: GenAM

Net-Probabilities

STEP 2					
NET-PROB	30.5%	59.9%	-19.8%	-64.8%	-5.8%
NET-RANK	2	1	4	5	3
FORECAST$_{adj}$	*TOP*	*TOP*	*BOTTOM*	*BOTTOM*	*MID*

TAA-Stance

STEP 3	
FORECAST$_{fin}$	*GV|CS ▲▼ IG|HY*

MODEL OUTCOME	overweight (▲): GV & CS underweight (▼): IG & HY stay neutral in EQ

Source: GenAM

Standard kNN can just classify one asset class at a time. The forecast is simply the performance category (TOP, MID, BOTTOM) with the highest probability. The probability in turn is the sum of weights[11] of the closest historical look-alikes assigned to that category. In our five-asset class approach this classification happens simultaneously across all asset classes using the same neighbourhood[12], enforcing consistency of the forecasted categories. I.e., two asset classes must be classified as TOP performers, two as BOTTOM performers, and one as a MID performer.

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[6] Please note that the structure of the benchmark is not relevant to compute the added value if the TAA range does not depend on the benchmark weights.
[7] In case of an even number of asset classes floor of n over two is equal to n/2.
[8] For an odd number of asset classes, the remaining asset class will be classified as "MID performer" and set to neutral in the TAA.
[9] Formally this is the combination five choose two, representing the number of ways to choose two top/bottom performers from five asset classes.
[10] Formally, this equals the number of ordered pairs of disjoint two-asset combinations: five choose two (representing the number of ways to choose two top/bottom performers from five asset classes) times three choose two (representing the number of ways to choose two top/bottom performers from the three remaining asset classes.)
[11] Weights are proportional to the inverse of the standard Euclidean distance between the neighbours and the forecast point.
[12] We achieve this by replicating each dataset four times, resulting in five datasets (one for each asset class at any given point in time). We introduce an identifier that is held invariant with respect to all transformations applied to the other (macroeconomic) variables with values constrained to the set {100, 200, 300, 400, 500} while all other variable range between 0 and 1 after transformations. This ensures that the identifier does not materially influence the choice made by the algorithm. I.e., it selects the same historical look-alikes for all asset-classes, while being constrained to at most one clone per point in time (i.e., no neighbour can be picked twice).

The visualisation on the previous page illustrates the basic mechanism using a hypothetical example. Standard kNN would just refer to one of the columns labelled as CS, GV, IG, HY, or EQ and stop after STEP 1.

Starting on the left, we are assuming a neighbourhood of four members (past episodes, i.e. months). Line-wise we have the realized return ranking of our five asset classes for each of the four members. A TOP performer is defined as having ranks 1 or 2, a MID performer has rank 3, and a BOTTOM performer has ranks 4 or 5. Focusing on CS, it receives rank 1 from the first and fourth nearest neighbours. Summing their weights yields an estimated probability of 52.9% that CS will be a TOP performer. We proceed in the same way across all performance categories for all asset classes. Identifying the highest probability by asset class, we end up with CS and GV expected to be TOP performers and IG, HY, and EQ expected to be BOTTOM performers. None of the asset classes is assigned to the MID category. I.e., the formula from page 3 to calculate the added value of a TAA based on the model outcome cannot be applied.

As the classifications are produced simultaneously yet estimated independently, the raw (“standard”) probabilities do not guarantee a consistent joint outcome. To address this, STEP 2 computes, for each asset, a net probability defined as the difference between the probability of being a TOP performer and that of being a BOTTOM performer. Although these quantities are no longer strictly interpretable as probabilities, they provide a consistent ranking across all asset classes.

In STEP 3 we simply translate the forecasted performance categories into a TAA stance by overweighting the two TOP performers (GV & CS) at the expense of the two BOTTOM performers (IG & HY). EQ is set to neutral.

Although the model produces a full cross-asset ranking, the current implementation only uses the categorical performance labels. Thus, conclusions regarding the ranking within each category are not supported in the current setting. However, further developments could leverage the full ranking (see chapter 4. Conclusions & Outlook).

Training Setup			
Data Trasformations		**Feature Selection**	
*EWMA**	over 2 Periods	*Excluded Groups*	
Scaler	MinMaxScaler		(1) Consumptions, orders and inventories
PCA	polynomial Kernel of degree 3		(2) Interest and exchange rates *(except for: 1Y-Treasury Rate)*
Crossvalidation Setup			(3) Prices
min training size	60 observations		(4) Stockmarket *(except for: VIX)*
first fold	TRAIN: 1992-10...1997-09 ► TEST: 1997-10	*# of remaining features*	72 out of 127
last fold	TRAIN: 1992-10...2021-11 ► TEST: 2021-12		
# of folds	291		
Optimal Results			
Model Parameters		**Outperformance****	
# of neighbours	12	*kNN*	+4.4 bps (+7.2 bps)
# of PCs	11	*Naïve*	+3.5 bps (+4.3 bps)

**Exponentially Weighted Moving Average; **Ø value per month, assuming return maximisation with constant TAA range of ±4pp; Naïve: EQ|HY ▲▼ GV|CS*
figures in brackets denote out-of-sample results (2022-01 – 2025-10)

2.2 kNN Setup

To determine the optimal composition of the neighbourhood, the algorithm is trained and tested across numerous combinations of variable selections and transformations over time. At the core of the training is the identification of the optimal neighbourhood size and the optimal number of principal components used to condense the information contained in the macroeconomic input variables[13] after excluding certain groups of variables[14]. The optimal configuration maximises the added value of a TAA based on the model outcomes across all folds[15] (see the table page 5).

3. Results

With respect to the data transformations (see the table on page 5), the optimal results are consistent with those obtained for our pairwise US model. The optimal settings for smoothing, scaling, and dimensionality reduction are identical. In-sample, a TAA strategy based on the model's outputs would have generated an average monthly outperformance of +4.4 bps. Out-of-sample, this figure is even higher at +7.2 bps[16].

3.1 Findings

Not only does the model add value relative to the benchmark, but it also outperforms a more challenging naïve allocation approach constantly overweighting EQ and HY (which over the long run tend to render high returns) at the expense of GV and CS[17] (see table on page 5). Over the past 33 years, the naïve approach captured the full TAA potential in 23% of months. Over the same period, it outperformed the benchmark in 25 calendar years. In eight of those 25 years, the kNN model still added additional value. However, the model's advantage is most evident in the eight years when the naïve approach underperformed the benchmark (due to risk-off spells that can be quite harmful).

<table>
<tr><th colspan="8">TOP 10 most rewarding Months</th></tr>
<tr><th rowspan="2">Rank</th><th rowspan="2">Month</th><th colspan="2">TAA Stance</th><th colspan="3">Outperformance vs BM*</th><th rowspan="2">Δ kNN (vs Naïve)</th></tr>
<tr><th>optimal</th><th>kNN</th><th>optimal</th><th>kNN</th><th>Naïve</th></tr>
<tr><td>1</td><td>2020-03</td><td>GV|CS ▲▼ HY|EQ</td><td>IG|GV ▲▼ CS|EQ</td><td>170</td><td>107</td><td>-170</td><td>277</td></tr>
<tr><td>2</td><td>2008-10</td><td>CS|GV ▲▼ HY|EQ</td><td>GV|CS ▲▼ IG|EQ</td><td>165</td><td>128</td><td>-165</td><td>294</td></tr>
<tr><td>3</td><td>2009-01</td><td>HY|IG ▲▼ CS|EQ</td><td>GV|CS ▲▼ IG|EQ</td><td>98</td><td>-5</td><td>45</td><td>-50</td></tr>
<tr><td>4</td><td>2009-04</td><td>EQ|HY ▲▼ GV|CS</td><td>GV|IG ▲▼ HY|EQ</td><td>89</td><td>-76</td><td>89</td><td>-164</td></tr>
<tr><td>5</td><td>2002-07</td><td>GV|CS ▲▼ HY|EQ</td><td>GV|IG ▲▼ HY|EQ</td><td>76</td><td>75</td><td>-76</td><td>151</td></tr>
<tr><td>6</td><td>2022-08</td><td>EQ|HY ▲▼ GV|CS</td><td>HY|EQ ▲▼ IG|GV</td><td>72</td><td>64</td><td>72</td><td>-7</td></tr>
<tr><td>7</td><td>2008-12</td><td>GV|IG ▲▼ CS|HY</td><td>GV|IG ▲▼ HY|EQ</td><td>71</td><td>67</td><td>-54</td><td>121</td></tr>
<tr><td>8</td><td>2011-08</td><td>GV|IG ▲▼ HY|EQ</td><td>EQ|HY ▲▼ CS|GV</td><td>68</td><td>-63</td><td>-63</td><td>0</td></tr>
<tr><td>9</td><td>2016-03</td><td>EQ|HY ▲▼ CS|GV</td><td>IG|GV ▲▼ EQ|CS</td><td>66</td><td>-31</td><td>66</td><td>-97</td></tr>
<tr><td>10</td><td>2001-03</td><td>IG|GV ▲▼ HY|EQ</td><td>IG|GV ▲▼ EQ|CS</td><td>65</td><td>62</td><td>-58</td><td>120</td></tr>
<tr><td colspan="3">Source: GenAM</td><td>Ø</td><td>94</td><td>33</td><td>-32</td><td>65</td></tr>
</table>

*Assuming return maximisation with constant TAA range of ±4pp; Naïve: EQ|HY ▲▼ GV|CS

The table above indicates that the largest TAA potentials coincide with risk-off periods in financial markets. As the naïve approach is always risk-on, the general ability of the kNN model to switch stance when risk sentiment sours pays off in these periods. E.g., in the top two periods (2020-03 and 2008-10), the naïve approach effectively erased

[13] For detailed information see our Core Matter: Machine Learning and Tactical Asset Allocation (Part II).
[14] Similarity in kNN is defined purely metrically, not content-wise. Variables that are thematically related do not necessarily improve the distance metric; redundant feature blocks can dominate distances and mask the regime signal. In contrast, regression models estimate parameters and can partially absorb redundant predictors via coefficients, whereas in kNN every additional (especially correlated/noisy) feature directly reshapes the neighbourhood structure. In kNN the focus is on robust generalization, unlike classical regression, where inference and coefficient stability are key concerns.
[15] A fold denotes a single train/test split within the rolling time-series validation.
[16] In sample: 1997-10 to 2021-12, out of sample: 2022-01 to 2025-10
[17] We operate under the assumption that taking risk pays off on average.

the available TAA potential, whereas the kNN model captured most of it. Across these top 10 most rewording months, the kNN model added an average of +33 bps, whereas the naïve approach gave up nearly the same amount.

3.2 Explainability & Diagnostics

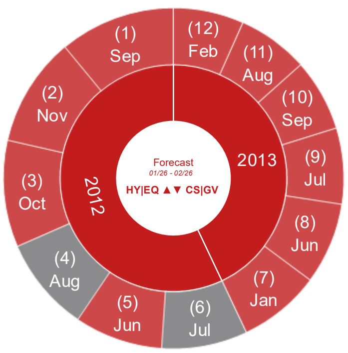
Apart from its versatility and robustness, intuitiveness and transparency are among the most appealing features of the kNN model.

We strive to avoid the "black-box" nature typically linked to machine learning. We have always been convinced that confidence in any model's results is crucial when it comes to applying them – especially when decisions depend on those outcomes. To strengthen this confidence and reduce uncertainty, we provide users with a transparent look behind the scenes of the signals generated by the ML algorithm. By offering as much background information as possible, we enable users to qualitatively assess each signal produced by the model.

As visuals generally communicate information more effectively than words, we developed a set of graphical representations already for the pairwise models[18]. Most of these visual tools also apply to the five-asset class model, though sometimes with a slightly different interpretation. Some representations are entirely new, reflecting the more complex nature of the expanded model.

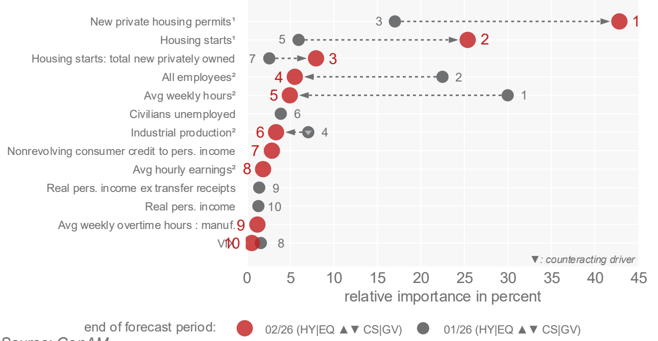
The sunburst (see left-hand chart below) visualizes the kNN result: each outer segment represents a historical nearest neighbour (look-alike) sized by its weight. In the pairwise models the colour shading (grey/red) encoded the neighbour's market regime. Summing weights by colour yields the forecasted regime and an implied confidence measure. In the five-asset class model we do have 30 potential "regimes". Thus, a two-colour encoding does no longer work. Each neighbour is now coloured by whether the forecasted regime (TAA stance) would have outperformed in that respective period: red = yes, grey = no. Thus now, summing the red segments gives us an implied confidence[19].

Current Neighbourhood Structure for the US



Source: GenAM
FRED-MD database status: early 01/26; red/grey segments in favour of/opposed to forecast; numbers in brackets denote the proximity rank

TOP10 Forecast Driver Dynamics for the US



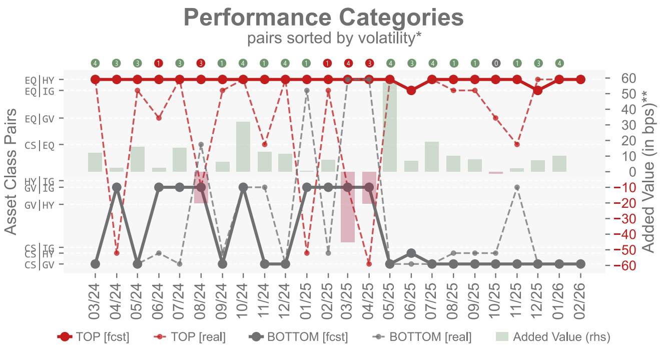
Source: GenAM
FRED-MD database status for last forecast: early 01/26; PCA loadings aggr. by rel. SHAP values; ¹sum across regions; ²sum across sectors

The dumbbell chart (see right-hand chart above) goes one step further by highlighting the macroeconomic drivers that most influenced the model's neighbourhood selection

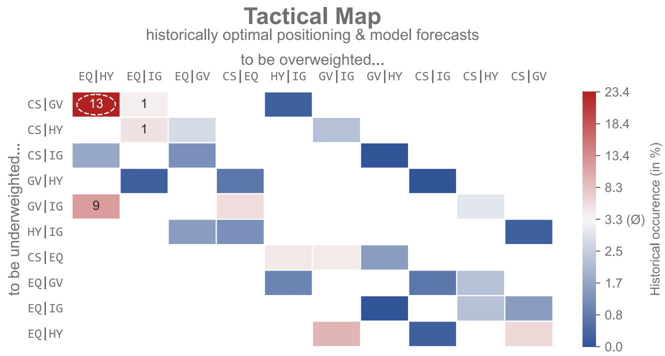
[18] For detailed information see our Core Matter: Machine Learning and Tactical Asset Allocation (Part II).
[19] Please note that the interpretation of the two implied confidences is slightly different as the weights in the five-asset class case affect the model outcome only through the net probability (s. chapter 2.1 From Classification to Ranking).

(ranked by importance and compared to the previous month) and thus, the forecasted TAA stance. The importance is derived from so called SHAP values. Counteracting drivers (here just "Industrial Production" ranked 4 in the previous month's forecast) indicate variables that work in the direction of lowering the implied confidence of the model forecast[20].

Taken together, the two charts on the previous page explain the model's signal – its structure and key drivers – and indicate its decisiveness.



Source: Datastream, GenAM
*historical, assuming equal weights, sorted in descending order; **return maximisation under constant TAA range of ±4 pp
Top Labels: Similarity Score: # of matches in minus # of mismatches between categories of forecast and realistion; range from -4 to +4, negative scores in red



Source: Datastream, GenAM
figures: number of forecasts within the past two years; circle: current forecast

For the pairwise model, a bar chart (see chart on the front page) was sufficient to show the model's success by plotting the return differential between EQ and GV and using green/red colouring to indicate whether the model was on the correct side. As a right-or-wrong assessment no longer applies after extending the model to five asset classes, we completely overhauled the chart.

In the left-hand chart above, the bars no longer show a return differential; instead, they show the added value of a TAA based on the model outcome. The green/red colouring now indicates outperformance/underperformance (right-hand axis). We also contrast the model's forecasted performance categories (solid lines) with the realised categories (dashed lines). With categories ordered in ascending order by historical volatility (left-hand axis), a red line (TOP performer) above its grey counterpart (BOTTOM performer) indicates risk-on; otherwise, risk-off.

As further information on the quality of the model's signal, we show a similarity score21 at the top of the chart. It ranges from −4 (very poor) to +4 (excellent). For readability, negative values are shown in red.

The heatmap (see right-hand chart above) shows the last two years of model forecasts in historical context. The x-axis lists the pairs of asset classes to overweight; the y-axis lists those to underweight. With both axes ordered in descending order by historical volatility, the top-left cell represents the most extreme risk-on case[22]. Cell colour encodes historical prevalence: the relative frequency of each case over the past 33

[20] Please note: SHAP values are computed for the principal components (PCs), not the original variables. Mapping these PC-level SHAP values back to individual variables requires the component loadings – straightforward for linear PCA, but not for kernel PCA. For more information on SHAP values and kernel PCA see our Core Matter: Machine Learning and Tactical Asset Allocation (Part II).
[21] Per period, we have a forecasted TOP and BOTTOM category and their realised counterpart. A match occurs if forecast and realisation for an asset-class agree within the same category (TOP or BOTTOM); a mismatch occurs if a forecasted TOP for an asset class shows up as a realised BOTTOM (or vice versa). The similarity score equals the number of matches minus the number of mismatches.
[22] Thus, the upper-left cell corresponds to EQ|HY ▲▼ GV|CS – the TAA stance underlying the naïve approach.

years[23]. The numbers in the cells show how often a model forecast fell into each case; the dashed ellipse highlights the current forecast. This gives a sense of how (a)typical the recent model forecasts are relative to their historical prevalence.

4. Conclusions & Outlook

Extending the kNN approach to a five-asset class universe materially enhances Tactical Asset Allocation by capturing cross-pair interactions that combinations of pairwise models miss. Using a single, shared neighbourhood and net-probability ranking delivers a consistent, transparent stance across EQ, HY, IG, GV and CS. Applying a ±4pp scope for active weights for each asset class, true out-of-sample tests (01/2022–10/2025) show the model outperforming +7.2 bps per month and achieving a ~75% success rate over the past two years[24], also outperforming a naïve, permanently risk-on tilt. Augmenting the established diagnostic visuals, such as neighbourhood structure and drivers, with new ones, including the added value view and the heatmap, further enhances interpretability of the model and strengthens user confidence.

For future work, we envisage three lines of development to broaden scope and deepen the kNN approach.

1. **Transfer of the model to the euro area (EA)**: like already done in the pairwise case, shifting the regional focus to the euro area is a natural next step for a euro-based investor. We will leverage the US work wherever feasible, mindful that the well-known caveats around data availability and quality for the euro area apply here too.

2. **Combining US and EA models:** assuming success in developing the euro-area model, a single model spanning both regions may prove rewarding. Apart from the usual model-training work, this will require substantial effort to combine and harmonise the two macroeconomic input datasets [25]. Furthermore, the large number of potential pairs and TAA stances may prove challenging, both computationally and for visualisation.[26]

Independent of these two proposals, the assumption of a constant TAA range could be relaxed.

3. **Explicit ranking consideration:** with a fixed TAA range, the model's ranking is effectively unused[27]; moving to a flexible, ranking-aware range that gives greater leeway to the outer ranks would allow us to express the forecasted TAA stance at the individual asset-class level rather than at the category level.

[23] Red indicates a relative frequency above average; blue indicates below. The darker the colour, the larger the deviation. White cells mark invalid combinations where the pairs are not disjoint (i.e., they share at least one asset class).
[24] Here, we refer to the last two years only to allow for a direct comparison with the results of our existing EQ|GV models shown on the front page.
[25] FRED-MD for the US and EA-MD-QD for the euro-area.
[26] Combining two five-asset class models for the US and EA would lead to nine asset classes in total (assuming that Cash is only maintained for the EA). The TOP and BOTTOM categories each now comprise four constituents (prev. two), yielding 126 possible compositions (prev. 10). The number of potential TAA stance will be up to 630 (prev. 30).
[27] As already said at the end of chapter 2.1 From Classification to Ranking: "Although the model produces a full cross-asset ranking, the current implementation uses only the categorical performance labels. Thus, conclusions regarding the ranking within each category are not supported in the current setting"

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