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Machine Learning approach to FX option trading: preliminary results

- Artificial Intelligence (AI) has gained a lot of popularity in recent years, notably thanks to developments in hardware and computing capacity, which have allowed the treatment of larger datasets and broadened real-world applications.
- Machine Learning (ML) is the branch of AI specifically devoted to predictive analysis: given a training set of inputs Y and outputs X, find the best fitting function f such that $f(Y) \approx X$. In the testing phase, apply the fit f to new inputs to make predictions.
- In this preliminary note we explore a ML – specifically Supervised Learning - approach to trade decision on 1M EUR/USD ATM options. We train standard ML models on a fairly large set of cross-asset and macro indicators to decide whether one should buy/sell/do nothing.
- Among the ML models we test, we find that k-Nearest Neighbors (kNN) and Support Vector Machines deliver the best predictive performances (>80% success rates in our implementations) when the dimensionality of the dataset is reduced through Principal Component Analysis (PCA).
- On the other hand Naïve Bayesian models and Decision Trees, which resemble the most how human experts form their decisions, fare more poorly.
- This intuitively validates the idea that dedicated ML models have the potential to outperform human discretion, especially when vast datasets are used. The framework best suited to trading decisions is to consider well defined global market states, rather than focus on a small set of determinant indicators.

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See page 7 for analyst certification and important disclosures.

Machine Learning: everybody else is doing it so why can't we?

The field of Artificial Intelligence (AI) has gone through several boom/bust cycles since Alan Turing pioneered the concept of "Universal Machine" in 1936. It has regained popularity in recent years, notably thanks to developments in hardware and computing capacity, which have allowed the treatment of larger datasets ("Big Data") and broadened real-world applications, with promises of driverless vehicles and increasingly obtrusive advertisement. Machine Learning (ML) is the branch of AI specifically devoted to predictive analysis: given a training set of inputs Y and outputs X, find the best fitting function f such that $f(Y) \approx X$. In the prediction phase, apply the fit f to new inputs to come up with a "best guess". This fit f may not be analytical or easy to interpret at all, and there is a vast range of ML methods that are tailored to different real-world problems. For instance: medical diagnosis may be best modelled by a decision tree algorithm ("if the patient has fever, check the throat for signs of infection; if not present, is there abdominal pain that could signal appendicitis, etc…"), Bayesian probabilities can be applied to assess the chances of Liverpool winning the Premiere League given that Chelsea was league leader on Boxing Day, Neural Networks have a solid track record in visual pattern recognition, etc.

In this note we explore basic ML approaches to **trade decision on 1M EUR/USD ATM options. The goal is to investigate whether one can efficiently train a vol trading automat** that would outperform our usually discretionary process of considering a (humanly manageable) narrow set of features from the vol markets - typically: nominal level and zscores of ATM vols, and implied vs realized vol risk premia - and incorporating in-house macro views. It is a Supervised Learning problem, as we feed the system with market data at inception and the corresponding option PNLs at 1M expiry. To simplify the problem, we slice the option PNLs in three classes: PNLs<-20bps correspond to "vol sells", PNLs>+20bps are "vol buys", and PNLs falling in-between are "neutral". **Given the historical track record, we look for the system to decide whether one should buy/sell 1M EUR/USD, or do nothing, when we feed it fresh data**. Note that a ML model trained on this specific classification problem won't be expected to make decisions on other trades, say when to buy/sell 3M 25D RRs in USD/CAD.

Data quality is critical to the robustness of ML classification, and it is often considered that it trumps the choice of particular algorithm. In fact the recent resurgence of AI owes a great deal to a shift from model-based to knowledge-based approaches. One needs to exercise a certain level of subjective judgment when forming the input dataset. With an agnostic view on what constitutes a good market dataset, we choose the set of 377 indicators detailed in Table 1, sampling from FX, rates, equities, commodities, and credit markets, as well as macro indicators (JPM's Economic Activity Surprise Indices) and IMM positioning. For each indicator we consider changes over 1w and 1M, which give a measure of **market dynamics and (implicitly) momentum/mean-reversion and cross-asset correlations**. We refrain from using daily moves as these would introduce synchronization issues among different asset classes – and also because IMM positions are not available on a daily frequency. For realised and implied vols, we also include nominal levels as inputs, as they have sufficient high-frequency variability and are less prone to stationarity than the other measures. The total historical range is 10Y, with daily samples, giving us 2609 datapoints (of 377 components each) in total.

Table 1: Our dataset consists of 377 indicators from FX and cross-asset markets as well as macro data

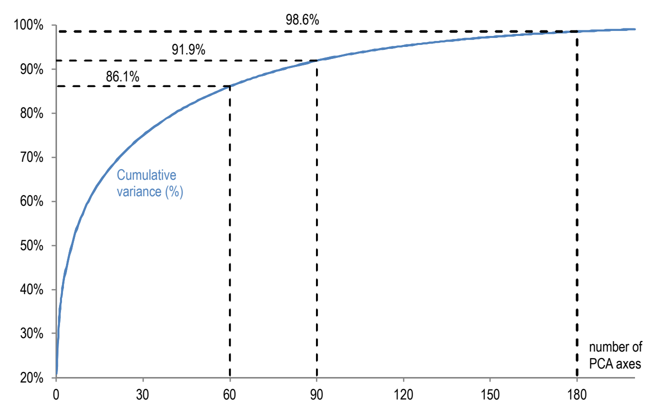
A total of 377 market indicators are formed across various asset classes. We use a 10Y history of these indicators, with daily sampling.

Market data type	Market data	Level	1 week change	1M change	Count
FX realised vols	2M realised vols in USD vs G10, MXN, BRL, ZAR, TRY, INR and KRW	X	X	X	45
FX ATM vols	1M, 3M and 1Y ATM in same pairs	X	X	X	135
FX skews	3M 25D RRs	X	X	X	45
FX spots	FX Spots in 15 G10 and EM USD pairs		X	X	30
Depo rates / Basis	3M FX Forward drops		X	X	30
Interest Rates	10Y Gov yields: US, Japan, UK, Germany, France, Italy, Spain, Australia		X	X	16
Equity Indices	S&P, Nikkei, FTSE, E-Stoxx, ASX, Mexbol, Bovespa, KOSPI, Hang Seng		X	X	18
Commodities	Gold and Brent spot		X	X	4
Credit spreads	CDX IG and HY, iTraxx spread indices		X	X	6
EASI indices	Global, US, CAD, EU, UK, CHF, NOK, SEK, Japan, AU, NZ, China		X	X	24
IMM positions	USD, EUR, JPY, GBP, CHF, CAD, AUD, NZD, MXN, RUB, Gold		X	X	24

Source: J.P. Morgan.

Figure 2: The dimensionality of the data is greatly reduced through a PCA, with 60 axes accounting for 86% of the variance

Share of total variance vs number of principal components of PCA applied to 377 large dataset.



Source: J.P. Morgan.

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More data more problems

Applying a PCA decomposition – which itself falls in the category of Unsupervised Learning methods, on the market dataset has several desirable properties. It is appealing to add as many data types as possible and train the algorithm on the whole set. After all, it would seem logical to think that the more information we gather on the market, the better. In reality, that is far from true. **Working with a high dimension set is prone to what is referred to as the "curse of dimensionality"**: 10Y worth of datapoints would form a dense set on a 2D plane, but span an extremely scarce set in a hyperspace of dimension 377. Consequently there are numerous acceptable (hypersurface) boundaries that can partition the dataset. In simple terms, if one is too ambitious about uncovering all the interactions between market inputs and their impact on trading decisions, there aren't enough samples in human history to train the models. In fact, there aren't enough atoms in the known universe ($\sim 10^{80}$) to populate a space of dimension 377 in a remotely dense fashion. Including more data types is not necessarily better. For that reason, and because it is intuitive to consider that market indicators are highly correlated across assets, **we want to advantage the models which performances are the highest after reduction of dimensions**. Such models are more likely to be tuning in to the main drivers of the markets. Note that there are other ways to address the curse of dimensionality, for instance by applying non-PCA feature selection/clustering to the dataset, or by "boosting" several ML models to derive a more robust combined predictor. We leave these (and other so-called Ensemble methods that operate at the meta-ML level) for further research.

Lies, damn lies and regressions

Just as the character of *Monsieur Jourdain* in Moliere's play was speaking prose without knowing it, finance practitioners have been routinely using a ubiquitous ML model to assess the value of market variables. Namely Ordinary Least-Square linear regressions (OLS) are standard prediction algorithms, and we use them ourselves in our short term FX fair-value models or to spot when the vol in one pair is cheap relative to another for example. Modern computing capacity makes it easy to extend linear regressions to large datasets, **however this would come with serious shortcomings and modelling fallacies**, notably:

- the OLS offers little flexibility: the fit of OLS methods is **highly biased due to the assumption of linearity to the underlying inputs**, which oversimplifies real-world interactions,
- it incorporates all data, **even those who are irrelevant to the output**,
- in its standard form, it is **sensitive to spurious outliers**,
- the R-Square always increases with the addition of new data, **potentially leading to misguided confidence in an overfitted model**,
- the **assumption of independent input variables is often violated in practice**. Correlation between inputs – which is unavoidable as more variables are included, leads to ill-defined betas and potentially large prediction errors,
- once trained, the OLS **always throws out a prediction for whatever given test data**. For instance, for a market scenario (S&P down -15% on the month, Oil up +3%, CDX IG 25bps tighter) , the trained model will give a definite output, even if it never encountered that instance before. A different ML model B might output: "I don't know, this is different from anything I've seen before". Another model C might decide: "I don't really need to know what Oil and credit are doing if S&P is down -15%, my decision is X". Thus different models look at the problem in different ways, and by ranking them we can get a clue as to which ML framework is most adapted to the trade decision problem at hand,
- not specific to OLS: combining data from different markets (for instance EUR/USD realised vols in % and 10Y US yields in bps) makes the model **highly sensitive to the scales in these data** and introduce convergence issues. In the analysis below we scale and normalize our input data, but also present the results for unscaled data for reference.

Extensions of OLS have been derived to deal with some of these shortcomings, and we notably find them within the class of Linear ML models (**Logistic Regression**, **Ridge regularization**, **Stochastic Gradient Descent**, **Passive Aggressive Classifiers**) and **Discriminant Analysis**. We apply these methods in turn to our problem of trade decision (buy/sell 1M EUR/ATM ATM, or do nothing). We also test other popular ML classification methods with non-linear assumptions: **Gaussian Naïve Bayes**, **Decision Trees**, **Support Vector Machines** – with linear and polynominal kernels, and **k-Nearest Neighbors**. Neural Network learning methods are left out for future research.

Running a beauty contest between ML models

In order to validate the ML models, we split the dataset chronologically into 80% (ie 8Y) **training** set, 20% (past 2Y) **test** set. Moreover **we run a *k*-fold cross-validation procedure** whereby the 8Y training set is randomly split in $k = 10$ samples of equal size. Each ML method is trained on 9 of those samples and tested on the remaining one, with the process repeated 10 times until all the samples have been tested once. On each repetition the accuracy score of the

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ML model is calculated (ie how often the model predicts the right “buy/sell/do nothing” trade), and the average scores are used to rank all the models. We report those cross-validation scores in Figure 3, for various preprocessing treatments of the input data. The first column shows the results for unedited raw data. The second column for data mean-adjusted and scaled by their standard deviations displays higher scores across the board, which reinforces the fact that ML models function better when they are fed information about the distribution of data rather than their nominal values. We are particularly interested in the results for data that undergo PCAs, as these are – partially – addressing the curse of dimensionality and explicitly exploit market correlations. While we haven't addressed whether the PCA is the best Unsupervised learning method to reduce the number of market features, both **kNNs** (with k=5) and **Support Vector Classifiers** perform the best when the dimensions are reduced (from 377 to 60), with accuracy scores exceeding 80%. On the other hand we find that Ridge and Logistic regressions, and LDA, are actually weakened by application of a PCA, which may suggest that these models perform a form of data pruning that is idiosyncratically more efficient than PCAs for linear models. There is a place for these models in trade decision, but their weakness to dimensionality reduction poses the risk that they may be overfitting.

Errare humanum est

Decision Trees (CART model) and Naïve Bayes models lag behind the classes of Neighbors and Support Vector Machines, regardless of the type of data preprocessing. **This is somewhat unfortunate, since Decision Trees in particular are easiest to interpret, and somewhat replicate how a human expert would form a knowledge-based decision**. Thus, given the extensiveness of the dataset we use - mixing more backward and forward looking technical and macro indicators than a human can possibly keep track of, and the fact that NB and CART models are devoid of human cognitive and emotional biases, this seems to spell bad news for the potential of human experts to generate high prediction hit rates by discretionary analysis of a dataset of limited size.

Top the class: kNNs and SVMs

Results on the 2Y test set are consistent with those of the training set, and we also find that kNN and SVM methods are the standout performers (Figure 4), returning 80%+ prediction accuracy. Reassuringly, the scores of the two models are resilient to and actually firmed up by application of a PCA to the dataset.

Figure 3: SVMs and kNNs achieve the best fits on the training dataset, when inputs are reduced through PCA

Average accuracies calculated by k-fold cross-validation – with k=10 - on the training dataset of size 8Y (years 2007-2014) for each ML algorithm considered in the study. First column shows the results using the unedited set of 377 market indicators. The second column shows results when marekt data are mean-adjusted and scaled by their standard deviations. Following columns show results for data reduced by PCAs of dimensions 180, 90 and 60, respectively. Methods are ranked according to the last column (PCA of dimension 60). We set k=5 in our implementation of the kNN method.

Class of ML Algo	Implementation	Raw Data	Normalised	PCA 180	PCA 90	PCA 60
Neighbors	kNN	65.5%	81.5%	81.4%	81.4%	80.9%
Support Vector Machine	SVC (linear kernel)	62.0%	77.3%	81.4%	81.8%	80.1%
Linear Model	Ridge	79.2%	78.8%	73.0%	70.6%	79.2%
Linear Model	Logistic Regression	78.9%	78.6%	74.0%	69.1%	69.9%
Discriminant Analysis	Linear Discriminant Analysis	80.3%	80.3%	72.9%	70.2%	69.6%
Decision Tree	CART	73.5%	72.9%	65.6%	67.7%	67.5%
Naïve Bayes	Gaussian NB	66.3%	67.0%	65.8%	66.0%	66.3%
Linear Model	PAC	43.3%	71.8%	67.7%	62.2%	43.3%
Linear Model	SGD	36.8%	70.7%	68.9%	63.2%	36.8%

Source: J.P. Morgan.

Figure 4: Once calibrated, SVMs and kNNs also perform the best on the out-of-sample prediction set

Prediction accuracies of each ML model on the test set of size 2Y (2014-2016). A tweak on the SVC (polynomial kernel of degree 3 rather than linear) brings marginal improvement. Ranking according to the last column.

Algorithm	Raw Data	Normalised	PCA 180	PCA 90	PCA 60
kNN	69.0%	83.9%	83.7%	83.3%	84.1%
SVC (polynomial kernel - degree 3)	59.5%	74.1%	82.4%	84.1%	84.1%
SVC (linear kernal)	62.1%	80.8%	83.3%	83.3%	82.4%
Ridge Regression	81.0%	80.8%	73.9%	68.4%	69.3%
Gaussian NB	67.2%	68.4%	69.2%	69.5%	69.3%
Linear Discriminant Analysis	81.2%	81.2%	73.4%	68.6%	68.2%
Logistic Regression	79.3%	79.9%	74.1%	68.6%	68.0%
CART Decision Tree	75.7%	76.1%	61.9%	68.6%	67.6%
PAC Regression	48.5%	76.6%	63.2%	65.7%	60.3%
SGD Regression	41.2%	76.4%	69.3%	64.9%	57.5%

Source: J.P. Morgan.

Figure 5: Breakdown of kNN performance on the prediction set

kNN model predictions vs actual outcomes. Precision scores indicate the percentage of prediction that are correct. For instance, kNN predicted "long" 54 times, and was corect 44 times, resulting in 81.5% precision for “long” decisions. Recall rates indicate how many times each category was accurately captured. Since there were 56 instances when “long” was the correct call, the recall rate for “long” is 78.6%.

		Predicted			
		Long	Neutral	Short	Recall
Actual	Long	**44**	12	0	78.6%
	Neutral	10	**288**	26	88.9%
	Short	0	35	**107**	75.4%
	Precision	81.5%	86.0%	80.5%	

Source: J.P. Morgan.

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The overall accuracy of a vol trading algorithm does not provide the whole picture of it effectiveness however. Due to traditionally rich risk premia, and asymmetrical payoffs between long and short vol positions, one would advantage a model that correctly predicts when to buy or sell with conviction, and only commits benign errors, such as predicting "long" or "short" when the outcome is “neutral" (false trading positives), or “neutral” when the outcomes is either “long” or “short” (missed trading opportunities). The more critical mistakes are of the form “long” instead of “short”, and vice versa. Fortunately the performance matrices of the two algorithms show no such critical mispredicts (Figures 4 and 5 for kNN and SVC respectively). In our experiment kNN has tended to made more polarized decisions (54 buy decisions and 133 sell decisions, vs 34/112 for SVCs) leading to less missed trading opportunities. This seems consistent to the way kNNs operate, employing a winner-take-all voting process in forming decision, although the boundary formation of SVMs can probably be fine-tuned to deliver similar performance.

Figure 6: Breakdown of SVC performance on the prediction set

		Predicted			
		Long	Neutral	Short	Recall
Actual	Long	**30**	26	0	53.6%
	Neutral	4	**304**	16	93.8%
	Short	0	46	**96**	67.6%
	Precision	88.2%	80.9%	85.7%	

Source: J.P. Morgan.

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