1. Introduction

Digital currencies have a number of advantages over a conventional equity market that companies can list upon. First, all cyrptocurrencies have a fixed supply and therefore will not suffer from devaluation as a result of quantitative easing, which is the case with conventional stocks (Gregoriou, 2022).[1] Second, trading in digital assets can generate excess returns for investors as reported by Gregoriou (2019). The abnormal returns persist once systematic risk, size, value, momentum, profitability and investment, are accounted for. Third, Zhang and Gregoriou (2020) provide evidence that in a period of high volatility, the cryptocurrency market bounces back very quickly. This implies that exchanges based upon blockchain technology are extremely efficient for investors.

Our objective is to develop a world-class rating system for crypto, DeFi and NFT-based assets. In order to accomplish this, we will utilize the latest Artificial Intelligence (AI) and Machine Learning (ML) methodologies, that are free from human bias. This is fundamental because the credit crunch financial crises of 2007-2009, was caused to a great extent by the failures of financial ratings. This is because financial ratings systems were dependent upon to some degree on human opinions and vested interests. Our ratings framework is entirely data driven by the latest techniques in financial modelling, which are free from any human intervention.

Ever since the use of AI/ML on the pricing of options conducted by Gregoriou, Healy and Ioannidis (2007), the application of ML in finance has grown along with increased computing power speed, memory capacity, and the vast amounts of data generated by modern financial markets. The development of “data science" as a distinct field has led to the recent development of numerous ML algorithms and their application to tasks such as portfolio optimisation, risk modelling, trend analysis, and sentiment analysis of news, amongst others. However, both regulators and many finance academics, perceive ML methods as "black-box" procedures, and are sceptical of “empirical" or “engineering" techniques. This is particularly true for predictions on asset prices, where the price and hence the future return of financial assets is estimated from a variety of factors.

[1] Professor Gregoriou provided written evidence to parliament concerning cryptocurrencies. This can be viewed at https://committees.parliament.uk/writtenevidence/111659/pdf/

For this reason, we cannot simply apply AI/ML techniques to the financial ratings of digital assets. This is because even though trading bots based on AI/ML can in principle make good predictions, they are not based on any fundamentals of asset pricing. The finance literature has established two broad established approaches to asset pricing over the last 60 years. Namely, work based on Expected Utility Theory and that drawing on “behavioral finance”. The first method assumes that investors are rational and will make investment decisions with the objective of maximising their expected utility. These decisions will involve making appropriate “trade-offs” between risk and expected return. This approach is exemplified by the Nobel Prize Winning research of Sharpe (1963, 1964) and Fama and French (1993, 2015) who developed the Capital Asset Pricing Model (CAPM) linking risk, as quantified by the standard deviation of market returns, and return in a way consistent with Expected Utility Theory. Subsequently, Florackis, Gregoriou and Kostakis (2011) extended and generalised the CAPM. They provide evidence based on UK data that liquidity is an additional risk factor that can explain expected returns. This research was presented to the Bank of England Financial Stability group in May 2010.

Although the Expected Utility Theory approach to asset pricing remains the dominant paradigm for academics and many market practitioners, the second approach, popularly referred to as “behavioral finance", is an important alternative and more a recent development. It rests on behavioural or cognitive models of decision-making under risk, and builds on insights from psychology, and neuroscience. These insights can be used to develop factors which can be used to price assets without necessarily assuming rationality on the part of market participants. However, arguably, the most seminal work in the behavioural area is that of (Kahneman and Tversky, 1979), who developed the Nobel Prize Winning Prospect Theory, and the related concept of reference dependence. One of the best-known examples of reference dependence is the Peak-End rule (Kahneman et al, 1993). Thus, it is reasonable to consider combining the Peak-End rule with factor models based on Expected Utility theory as a benchmark for our empirical work.

Our selection of factors follows the work of Gregoriou, Healy, and Le (2019) who tested the asset pricing performance of the Peak-End rule, and thus of Prospect Theory. Their results confirmed that peak-end behaviour by investors occurs and is not captured by factor models based on Expected Utility Theory. Their proposed seven factor pricing model, incorporating the insights of both Expected Utility theory and Prospect Theory, outperforms other popular factor models in explaining portfolio returns

The AI/ML Methodology

ML is a sub field of AI, and encompasses a large and varied set of algorithms, suited to different tasks. In our cryptocurrency financial ratings model we are concerned with Supervised Learning, and the task is regression. This is because our response variable is the returns of each digital currency and our explanatory variables are the factors, which come from Nobel Prize Winning academic research, discussed in the previous section. The AI/ML techniques provide the optimum fit of the factors which influence the ratings. This gives the advantage of the superior fit and unbiased estimation, while avoiding the black box problems of these methods.

There are many algorithms suitable for this task, and even more variants of each of these algorithms. Typically, ML algorithms have numerous hyper-parameters that require tuning. This is especially true of Deep Learning (Deep Neural Networks), which require considerable expertise to implement effectively. For each token that we rate, we estimate a number of ML algorithms, and the data selects the optimum method for each token. This is state of the art technology, supported by financial theory and free from human bias. Specifically, we compute the Distributed Random Forest (DRF), Extremely Randomised Trees (XRT), General Linearised Models (GLM), Gradient Boosting Machine (GBM), Deep Learning (Neural Networks) and Stacked Ensembles. There follows a brief description of each algorithm.

DRF

Distributed Random Forest (DRF) is a tree-based classification and regression tool (Breiman, 2001). When given a set of data, DRF generates a "forest" of classification or regression trees, rather than a single classification or regression tree. Increasing the number of trees will reduce the variance, without increasing the bias. Both classification and regression take the average prediction over all of the trees generated to make a final prediction. For our regression estimation, it will take a numeric value.

XRT

In random forests, a randomly selected subset of data features (variables) is used to decide on the splitting rule for each branching. In extremely randomized trees (XRT), a random subset of candidate features is also used. However, thresholds are also drawn at random for each data feature, and the best is picked as the splitting rule. This allows a further reduction in the variance of the model, but at the cost of a small decrease in efficiency.

GLM

A generalized linear model (GLM) as its name suggests, is a generalization of ordinary linear regression (OLS) that allows the dependent (response) variable to have a non-normal error distribution. In a GLM the linear model is related to the response variable by a link function and by permitting the variance of each measurement to be a function of its predicted value. In a GLM, each value, Y of the response variables is assumed to follow an exponential distribution, which could be e.g. a normal, binomial, Poisson, gamma or other exponential distribution. The mean, μ, of the distribution depends on the independent variables, X, through:

$$E(Y|X) = \mu = g^{-1}(X\beta)$$

Where $E(Y/X)$ is the expected value of Y given X, and β is a vector of unknown parameters. g is the link function. The variance of each measurement is given by;

$$Var(Y|X) = V(g^{-1}(X\beta))$$

Any of Maximum Likelihood, Maximum Quasi-Likelihood, or Bayesian techniques can be used to estimate the parameters β, and the V may be from any exponential distribution (see among others, Friedman et al, 2010). GLM's can be used for prediction or classification.

GBM

Gradient Boosting Machines can be used for both regression, and classification tasks. They are an ensemble modelling technique based, usually, on decision trees, which produces an ensemble of weakly predictive models. Gradient boosting combines these weakly predictive models into one strongly predictive model by an iterative process. Suppose we run the algorithm for m iterations. Each run produces an imperfect model

$$F_m(x) = \hat{y}_m.$$

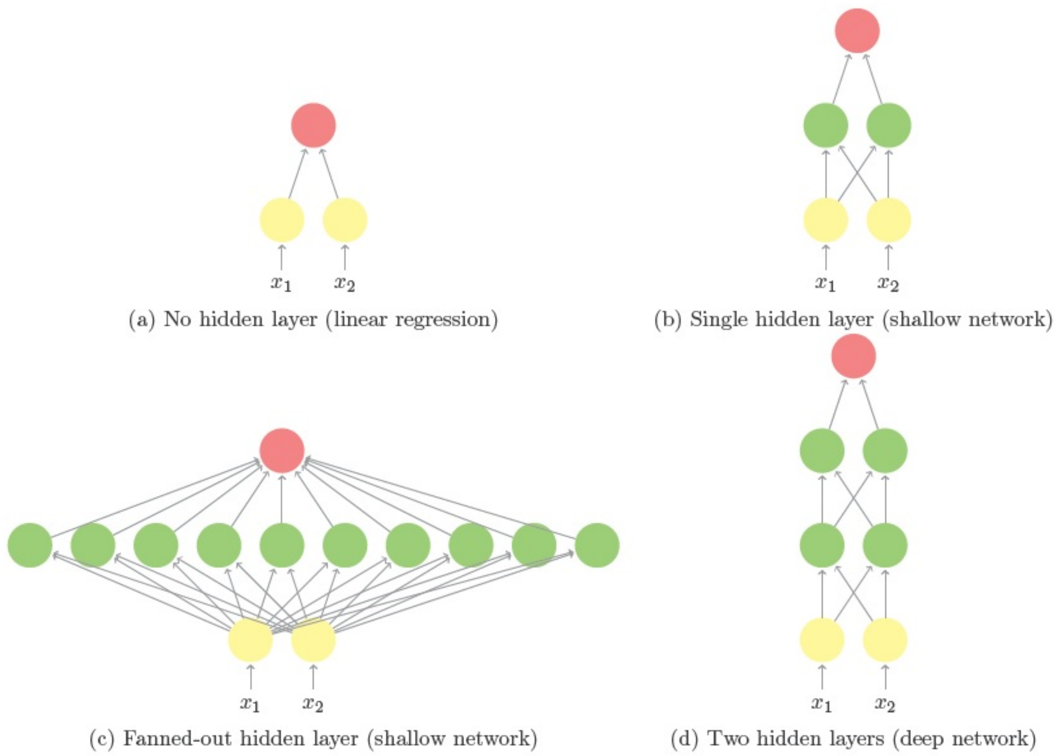
The next iteration will improve this estimate by appending another estimator, thus:

$$F_{m+1}(x) = F_m(x) + h_m(x) = \hat{y}_{m+1}$$

Where $h_m(x) = y - F_m(x)$. Thus, gradient boosting fits h to the residuals $y - F_m(x)$. Each iteration F_{m+1} therefore improves on the estimate of the previous iteration F_m, by minimising the loss function (see among others, Hastie et al, 2009).

Deep Learning

Deep Learning networks are a form of Artificial Neural Network (ANN) containing multiple hidden layers. In recent years, the term "Deep Learning" has become synonymous with "neural network". Kolmogorov (1957) in his representation theorem, showed that an ANN with a single hidden layer can approximate any Borel measurable function. In their seminal papers Hornik, Stinchcombe, and White (1989) and (1990), showed an ANN with a single hidden layer is capable of arbitrarily accurate approximation to any function and its derivatives, to any desired degree of accuracy, provided sufficiently many hidden units are available. This class of network is now referred to as a “shallow network" (Fig. 1 (c)). Whereas, the term “deep network" refers to ANN’s with multiple hidden layers.



Source: Dixon, Francis and Halperin (2019)

Fig. 1 Neural Network Architectures

Deep Learning has become popular in finance because it can handle high dimensional inputs. The principal advantage of Deep Learning however is computational speed and efficiency (Dixon and Polson, 2019).

Factors and Mechanism of the Ratings System

Factors

Liquidity

This measures the ability to trade a token, quickly, anonymously with little price impact. If there is a lack of liquidity, this is additional risk for an investor resulting in greater expected returns and vice versa. In conventional financial markets, liquidity can be measured via the bid-ask spread, which is the compensation that market makers receive for providing a financial market. This measure is not directly applicable to digital assets, given that they use automated market makers that process trades through the liquidity pools. A liquidity pool is a large number of cryptocurrency tokens locked in a smart contract, that are used to facilitate trades if the tokens are listed on a decentralized exchange.

According to Le and Gregoriou (2020) analysing the impact upon liquidity in terms of bid-ask spread is best applied to short-term effects while for longer terms effects of shocks, metrics based on daily returns and volume are viewed as appropriate. In light of the above, and as our data set incorporates time series analysis, we have applied the Amihud (2002) illiquidity ratio, used recently in Gofran, Gregoriou and Haar (2022):

$$RtoV = \frac{1}{Di}\sum_{d=1}^{Di}\frac{|Ri,d|}{Vi,d}$$

Where, $|R_{i,d}|$ and $V_{i,d}$ represent the absolute return and monetary volume of crypto i on day d respectively and D_i is the number of trading days for cyrpto i. The limitations of the illiquidity ratio RtoV should be noted: According to extensive research the Amihud illiquidity ratio involves size biasedness, since the monetary volume being used is directly correlated with market capitalisation. To overcome this, Florackis, Gregoriou and Kostakis (2011) introduced a new liquidity measure RtoTR which controls for size biasedness:

$$RtoTR = \frac{1}{Di}\sum_{d=1}^{Di}\frac{|Ri,d|}{TRi,d}$$

Where, $TR_{i,d}$ represents the turnover ratio of cyrpto i at day d, D_i and $R_{i,d}$ are the same as the Amihud ratio shown above. $RtoTR_i$ does not involve any size biasedness as monetary volume is replaced by the turnover ratio. This is because there is no significant association between turnover and market capitalization. We apply both price impact ratios as our measures of liquidity for completeness and cross comparisons.

Sentiment

These are psychological based indicators that investors use as a trading strategy, including the Fear and Greed index for digital currencies. We also develop are own sentiment measure by analysing the tones of each tokens' social media news to assess the relative weight of risks versus opportunities in their news feeds. Specifically, using the business-context dictionary developed by Loughran and McDonald (2011) to identify positive and negative words, we compute the net tone (sentiment) of social media disclosures. We calculate the sum of positive (negative) words divided by total words in the news feeds.

Volatility

Volatilty measures the risk of each token, the greater the risk the higher the expected return and vice versa. We measure volatility using a variety of methods, these include rolling variance and Generalized Autoregressive Conditional Heteroscedasticity (GARCH) models. We also incorporate the fat tails in the distribution of digital currencies through skewness and kurtosis due to extreme good and bad news, using the methodology in Wang et al (2021). Volatility is captured over rolling 1, 5, 10 and 30 day windows.

Momentum

Momentum encapsulates the rate of change of tokens over time, as it captures upward and downward trends in prices. This is integrated into our data using two different methods. First, we use a moving average of prices over a 1, 5 and 30 day event window. Second, we incorporate the peak end variable created by Gregoriou, Healy, and Le (2019). The peak is defined as the highest price of the token in the last month and the end is the last price.

Market Risk

This measures how the token is performing with respect to the CCi30 index, which includes the 30 largest digital currencies with respect to market capitalization.

Market Value

This is defined as the current price multiplied by the circulating supply. Market value is an important determinant of crypto-asset value and demand. This is because tokens with high market value, generally perform well and are regarded as a less risky investment.

How the ratings work

The data comes directly from the Coinbase cyrptocurrency exchange and is fed into our Python program via an API. We then compute the Distributed Random Forest (DRF), Extremely Randomised Trees (XRT), General Linearised Models (GLM), Gradient Boosting Machine (GBM), Deep Learning (Neural Networks) and Stacked Ensembles Models. We assign the AI/ML model which provides the best fit of the data for each token. Therefore, for each token all the AI/ML models are computed and the one with the optimum fit of the data is chosen. This varies for each token and at different points in time for the same token. This approach lets the data decide the best prediction and is free from any kind of human bias. We then allocate the ratings based on the following criteria.

Decision Rule	Cyrptocurrency Rating
Return > 0 > Previous Return	A rating
Return > 0 < Previous Return	B rating
Return < 0 > Previous Return	C rating
Return < 0 < Previous Return	D rating

The ratings are calculated on a daily basis but can be made available to update every three hours. We are rating 99 digital currencies, based on market capitalization. The objective is to rate all digital currencies and eventually all liquid assets and commodities and at 4 times during the day.

Our Automated AI/ML models perform remarkably well with respect to forecasting the prices of tokens. We provide daily, 5 and 30 day forecasts with accuracy of 95-99%.

References

Amihud, Y., 2002. Illiquidity and stock returns: cross-section and time-series effects. *Journal of financial markets*, *5*(1), pp.31-56.

Breiman, L., 2001. Random forests. *Machine learning*, *45*, pp.5-32.

Fama, E.F. and French, K.R., 1993. Common risk factors in the returns on stocks and bonds. *Journal of financial economics*, *33*(1), pp.3-56.

Dixon, M.F. and Halperin, I., 2019. The four horsemen of machine learning in finance. *Available at SSRN 3453564*.

Fama, E.F. and French, K.R., 2015. A five-factor asset pricing model. *Journal of financial economics*, *116*(1), pp.1-22.

Florackis, C., Gregoriou, A. and Kostakis, A., 2011. Trading frequency and asset pricing on the London Stock Exchange: Evidence from a new price impact ratio. *Journal of Banking & Finance*, *35*(12), pp.3335-3350.

Friedman, J., Hastie, T. and Tibshirani, R., 2010. Regularization paths for generalized linear models via coordinate descent. *Journal of statistical software*, *33*(1), p.1

Gofran, R.Z., Gregoriou, A. and Haar, L., 2022. Impact of Coronavirus on liquidity in financial markets. *Journal of International Financial Markets, Institutions and Money*, *78*, p.101561.

Gregoriou, A., 2019. Cryptocurrencies and asset pricing. *Applied Economics Letters*, *26*(12), pp.995-998.

Gregoriou, A., Healy, J. and Ioannidis, C., 2007. Hedging under the influence of transaction costs: An empirical investigation on FTSE 100 index options. *Journal of Futures Markets: Futures, Options, and Other Derivative Products*, *27*(5), pp.471-494.

Gregoriou, A., Healy, J.V. and Le, H., 2019. Prospect theory and stock returns: A seven factor pricing model. *Journal of Business Research*, *101*, pp.315-322.

Hastie, T., Tibshirani, R., Friedman, J., Hastie, T., Tibshirani, R. and Friedman, J., 2009. Boosting and additive trees. *The elements of statistical learning: data mining, inference, and prediction*, pp.337-387.

Hornik, K., Stinchcombe, M. and White, H., 1989. Multilayer feedforward networks are universal approximators. *Neural networks*, *2*(5), pp.359-366.

Hornik, K., Stinchcombe, M. and White, H., 1990. Universal approximation of an unknown mapping and its derivatives using multilayer feedforward networks. *Neural networks*, *3*(5), pp.551-560.

Kahneman, D. and Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica*, *47*(2), pp.363-391.

Kahneman, D., Fredrickson, B.L., Schreiber, C.A. and Redelmeier, D.A., 1993. When more pain is preferred to less: Adding a better end. *Psychological science*, *4*(6), pp.401-40.

Kolmogorov, A.N., 1957. On the representation of continuous functions of many variables by superposition of continuous functions of one variable and addition. In *Doklady Akademii Nauk* (Vol. 114, No. 5, pp. 953-956). Russian Academy of Sciences.

Le, H. and Gregoriou, A., 2020. How do you capture liquidity? A review of the literature on low-frequency stock liquidity. *Journal of Economic Surveys*, *34*(5), pp.1170-1186.

Loughran, T. and McDonald, B., 2011. When is a liability not a liability? Textual analysis, dictionaries, and 10-Ks. *The Journal of finance*, *66*(1), pp.35-65.

Sharpe, W.F., 1963. A simplified model for portfolio analysis. *Management science*, *9*(2), pp.277-293.

Sharpe, W.F., 1964. Capital asset prices: A theory of market equilibrium under conditions of risk. *The journal of finance*, *19*(3), pp.425-442.

Wang, A., Hudson, R., Rhodes, M., Zhang, S. and Gregoriou, A., 2021. Stock liquidity and return distribution: Evidence from the London Stock Exchange. *Finance Research Letters*, *39*, p.101539.

Zhang, S. and Gregoriou, A., 2020. The price and liquidity impact of China forbidding initial coin offerings on the cryptocurrency market. *Applied Economics Letters*, *27*(20), pp.16951698.