Whitepaper

Intelligent and unbiased crypto ratings
for the Web3 era of investment.

Crypto Ratings

Abstract

Evai is pioneering a world-class decentralised rating system for Crypto, DeFi and NFTs that can be used by anyone to evaluate these new asset classes. Through a combination of peer-reviewed financial research and economic modelling, Evai provides decentralised and impartial ratings based on a multi-factor AI & machine learning model removing human bias.

Introduction

Evai was created as a response to the financial crisis of 2008 which initiated the phenomenon of ‘Quantitative Easing’ (QE). QE has expanded money supply at the fastest rate since records began and has become a policy response to all economic headwinds that we face, including the economic downturn brought about by the Covid pandemic.

When we look back at the 2008 financial crisis, we can see that one of the major causes was the misallocation of assets resulting from incorrect ratings being attached to high-risk assets. It is therefore apparent that accurate ratings play a key role in fostering stability within our financial system.

With the advancement of technology, we are now able to harness the power of Artificial Intelligence and machine learning to deliver truly decentralised ratings, free from human bias, based upon a solid foundation of Nobel Prize winning academic theory.

Evai is delivering an unbiased financial ratings system that can theoretically be applied to all liquid asset classes. When accurate ratings are applied to the current 20,000+ digital assets that make up the crypto ecosystem, the resultant ratings can be used to reliably inform asset allocation. Furthermore, Evai ratings have been empirically tested and proven to offer predictive value, with the implication that investors may be able to exploit exceptions to the widely accepted “Efficient Market Hypothesis.”

Such an advancement in ratings technology adds value at every level from educational and regulatory through to market efficiency and profitability.

Founder’s Statement

The Evai project was conceived following the 2008 financial crisis, when it became clear that centralisation of power tends to lead to abuse of that power.

Evai has been established in order to ‘level the playing field’ and give equal opportunity to investors both big and small, through education and empowerment with freely available, unbiased financial ratings information.

May God bless our endeavour.

Problems Identified

The absence of an impartial rating system.

Ratings often determined by human analysts.

There is no universally accepted source of reliable data.

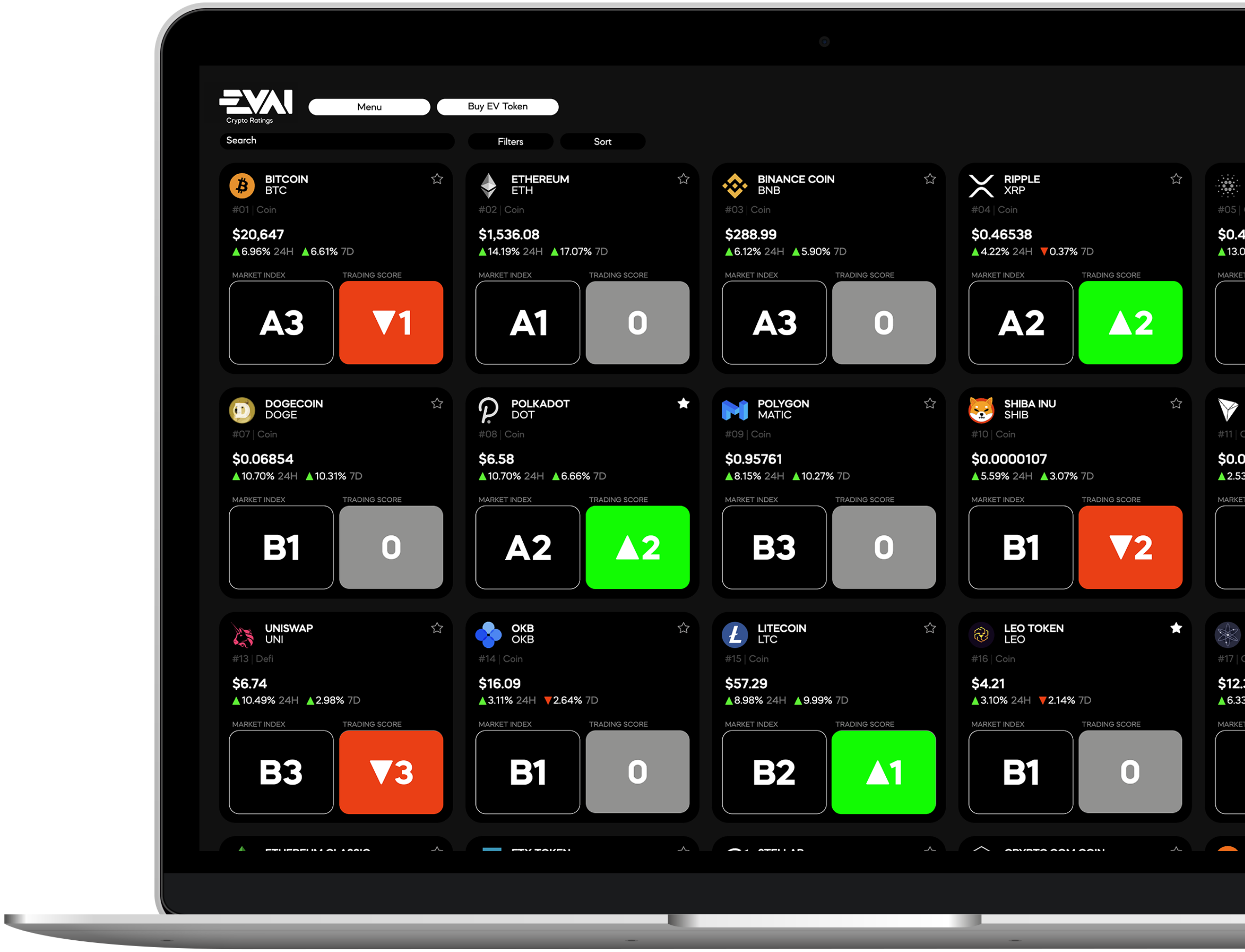
Evai Crypto Ratings is the answer

The Evai Crypto Ratings are built on the understanding that investors want to make smart decisions about crypto investments. Investors need the best information about which crypto assets to invest in and when.

There is a lot of noise, a lot of bad data, market manipulation, and other hidden risks with crypto assets and NFTs which can make investors feel unprepared to make the right decisions. Each of the crypto assets we rate undergoes a rigorous evaluation driven by AI and Machine Learning that dynamically scrutinises live market data.

Evai Crypto Ratings look at six performance factors and over twenty performance indicators before a rating is awarded. Unlike other crypto rating agencies, our data and research does not rely solely on the "expertise" of human inputs allowing us to share an unbiased rating with users to help them make informed decisions that maximise profits and minimise risk.

We believe that everyone, not just insiders and statistical experts, should benefit from the crypto market. We understand people want to benefit from the financial freedom crypto investments can provide without having to dedicate all of their time to evaluating the many risks and opportunities.



Evai Ratings

The 2008 financial crash was caused by a failure of financial ratings led by centralised ratings agencies. Evai ratings are completely free from human intervention, empowering retail and institutional investors worldwide.

The role of AI & machine learning

The Evai Crypro Ratings platform is a revolutionary product that combines the most important finance research over the past 50 years with a ratings framework free from human bias. Data drives the ratings and the AI/ML element is used to ensure the optimal data fit, delivering the most accurate ratings of cryptocurrencies to the end-user.

The AI/ML methodology is free from human bias and provides a superior data fit than conventional regression analysis. There is evidence of this in the option pricing market through the research conducted by Gregoriou, Healy and Ioannidis (2007). However, the AI/ML methodology also has its challenges. We will discuss all of the shortcomings of the AI/ML method and how we solved them for our ratings platform. We ensure that we obtain the best fit of the data, while our model is free from human bias and robust to the shortcomings of the AI/ML methodology.

Overcoming limitations

One of the fundamental issues with AI/ML is a lack of a theoretical model. This implies that we do not know which factors are driving the results. Also, AI/ML often overfits the data suggesting that noise becomes a factor in the model. These factors cause bias in the results from an estimation perspective.

We overcome these issues because our ratings platform is built on the theoretical models published in internationally recognised journals by Florackis, Gregoriou and Kostakis (2011) and Gregoriou, Healy and Le (2019). Their models extend the research of Fama and Kahneman, who are Nobel Prize winners. Second, given that we have a theoretical model, we have less noise than if we simply derived the ratings using AI/ML. This ensures that the overfitting problem associated with using the AI/ML method in isolation is substantially reduced.

The third problem of the AI/ML methodology is concerned with the quality of the data. We find in the digital currency market that data from exchanges is significantly skewed. This could lead to estimation problems resulting in loss of accuracy in the ratings platform. In order to overcome this issue, we ensure that our critical values used to determine our significance tests are robust to data skewness. This is accomplished by deriving our own critical values from an empirical distribution using the wild bootstrap applied in Arghyrou and Gregoriou (2007, 2008) and Gregoriou (2014).

Finally, we cannot derive the significance of factors with the use of AI/ML methods since they do not follow a conventional distribution. We overcome this problem by using regression techniques to establish statistical significance. We then apply the AI/ML techniques to give us the best data fit by computing the optimum weights of all the significant factors in our model.

Overview of the Ratings Process

The first level of financial ratings is univariate, where the rating will be based on a single factor.

The second level of financial ratings is more complicated, represented by the multi-factor model developed in Gregoriou (2011) and Gregoriou (2019) on asset pricing. In the multi-factor model, the cryptocurrencies are rated on excess returns, after accounting for multiple factors.

Evai will use both rating levels for comparison purposes in constructing a unique, comprehensive digital asset rating model.

In terms of data, we will use multiple data sources, which will be in tandem with our own proprietary data gathering techniques.

The resultant 'clean' data is then used to update the ratings model frequently. In instances where we do not have a complete information set, we will provide a shadow rating, which will be based on incomplete data and make this clear to the market. In instances where the data is insufficient, or we deem it unreliable, we will award a 'U' rating to the crypto asset.

Univariate (Single Factor) Ratings

We have 9 main factors in the univariate framework, with a further 12 factors in the multivariate framework, giving us 21 factors overall.

Liquidity	Composed by the following indicators: Turnover Ratio, Adjusted Turnover Ratio, Amihud Ratio, FKG ratio (Gregoriuet al, 2011), Roll Spread, Effective spreads, Quoted Spreads. Seven indicators overall.
Sentiment	Composed by Fear & Greed Index, Social Development History Index. Two indicators overall.
Volatility	Sharpe Ratio, Sortino Ratio. Two indicators overall.
Momentum	Moving Average, Rate of Change. Two indicators overall.
Utility	Firm Profitability - Proxy ROI. One indicator overall.
Behavioural Bias	Peak End Value Demand. One indicator overall.
Overextension	Fibonacci Retracements, Ichimoku Cloud, Bollinhger Band, Stochastic Oscillator. Four indicators overall.
Market Risk	Market Factor. One indicator overall.
Capitalisation	Size. One indicator overall.

Multi-Factor Ratings

The multivariate financial rating models will be the unique contribution of Evai, aiming to design a multi-factor model for cryptocurrencies. The model is based on Gregoriou et al (2019), where financial ratings are a function of systematic risk, firm size, profit, investment, sentiment, peak, end and liquidity. This seven-factor model has been developed for the equity market (Gregoriou A., J.V. Healy, H. Le, 2019).

Initially, the rating model includes only the following indicators: Amihud Ratio, (Liquidity), Fear & Greed Index (Sentiment), Sharpe Ratio (Risk), Moving Average (Momentum), Firm Profitability - Proxy – ROI, Utility, Peak End. The rating model will constantly improve, with additional factors added, and the methodology will be tested across different digital assets and portfolios.

Our model will optimise against the daily return on investment.

Evai ratings model

INPUTS TO THE MODEL
Crypto exchanges (markets) for data

- Data sourced directly from exchanges.
- Multiple exchanges are utilised.
- Inputs from the market.
- No rating provided when the data is insufficent or unreliable.

DATA USED IN MODEL DEVELOPMENT & CALIBRATION
Artificial Intelligence will determine the best statistical way to represent the average value for all VARIABLES included in the ratings gathered from different crypto exchanges.

MARKET INDEX
Updated every week (Sunday 01:00)

VOLATILITY
UTILITY
LIQUIDITY
MARKET CAPITALISATION
SENTIMENT

Sharpe Ratio · Sortino Ratio
Proxy ROI
Amihud Ratio · Adjusted Turnover Ratio · FKG Ratio · Turnover Ratio · Roll Spread · Effective Spreads · Quoted Spreads
Market Cap
Fear & Greed index · Social History Index

The factors that are currently being implemented are highlighted in black.

GLOBAL DAILY TRADING SCORE
Rating based on multifactor (most statistically significant factors) rating

A. Calculating the factor value scientific methodology
B. Conversion of global index values into a rating scale

Ratings will be result of the decile where the coin proxy[1] for the underlying value is positioned compared to the market index. This rating ranks the coins against Evai market index and classifies them in deciles, i.e. Top decile – rated as A1 to 10th decile rated as D.

A1 | A2 | A3 | B1 | B2 | B3 | C1 | C2 | C3 | D
Coins are ranked & classified in deciles, i.e Top decile - rated as A1 to 10th decile rated as D.

RATING METHODOLOGY CYCLE
Review of indicators

Rigorous tests to quantitive valuations and ratings will be processed to examine their performance.

Especially for the seven factor pricing data test will be performed to compare actual cryptocurrency performance against the performance expected at the time of review.

UPDATING CURRENCY PORTFOLIO
Portfolio review

Portfolio reviews offer a means of identifying new cryptocurrencies. Dedicated analytical staff for monitoring the performance of existing cryptocurrencies and identifying new cryptocurrencies.

INPUTS TO THE MODEL
Crypto exchanges (markets) for data

- Data sourced directly from exchanges
- Multiple exchanges are utilised
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DATA USED IN MODEL DEVELOPMENT & CALIBRATION
Artificial Intelligence will determine the best statistical way to represent the average value for all VARIABLES included in the ratings gathered from different crypto exchanges.

TRADING SCORE
Updated every 4 hours

UNIVARIATE RATINGS
Rating based on a single factor

Formulas for calculating a single factor's values are a result of a combination of the most advanced quantitative scientific research and analyst-driven output. All factors are unique and will have a unique rating schedule that will decide the rating scale of cryptocurrencies according to the corresponding value of each factor at a specific time.

A1 Exceptionally Strong	**A2** Very Strong	**A3** Strong
B1 Good	**B2** Moderately Weak	**B3** Weak
C1, C2, C3 Very Weak	**D** Distressed	**U** Unrateable

LIQUIDITY
SENTIMENT
VOLATILITY
MOMENTUM
UTILITY
BEHAVIOURAL BIAS
OVEREXTENSION
MARKET RISK
CAPITALISATION

Amihud Ratio · Adjusted Turnover Ratio · FKG Ratio · Turnover Ratio · Roll Spread · Effective Spreads · Quoted Spreads
Fear & Greed index · Social History Index
Sharpe Ratio · Sortino Ratio
Moving Average · Rate of Change · MACD
Proxy ROI
Peak End Value Demand
Fibonacci Retracement · Ichimoku Cloud · Bollinger Band · Stochastic Oscillator · Relative Strength Index · Future integration
Market Factor · Treynor Index · Future integration
Size · Future integration

The factors that are currently being implemented are highlighted in black.

TEST THE RATINGS

INDIVIDUAL DAILY RATING SCORE (IRS)

INDIVIDUAL DAILY TRADING SIGNAL

GLOBAL DAILY TRADING SCORE
Rating based on multifactor (most statistically significant factors) rating

A. Calculating the factor value scientific methodology
B. Conversion of global index values into a rating scale.

Evai's unique methodology based on Gregoriou (2011) & Gregoriou (2019) work on asset pricing, where ratings are a function of liquidity, investment, systematic risk, profit, peak-end and firm size.

Symbols "+"/ "-"/ "0" show the direction of the daily movement in the coin global performance. This direction is meaningful as "+" indicates a buy, "-" a sell and "0" a hold strategy). The number accompanying the symbols "+"/ "-"/ "0" shows the strenth of the trading signal for the specific coin.

Plus (+) and (–) symbols will indicate the likelihood of a positive or negative performance direction, while the numbers 1–3 will deliver a 4 hourly trading strength score relating to each asset.

0 = No Change
1 = Low
2 = Medium,
3 = High

RATING METHODOLOGY CYCLE
Review of indicators

Rigorous tests to quantitive valuations and ratings will be processed to examine their performance.

Especially for the seven factor pricing data test will be performed to compare actual cryptocurrency performance against the performance expected at the time of review.

UPDATING CURRENCY PORTFOLIO
Portfolio review

Portfolio reviews offer a means of identifying new cryptocurrencies. Dedicated analytical staff for monitoring the performance of existing cryptocurrencies and identifying new cryptocurrencies.

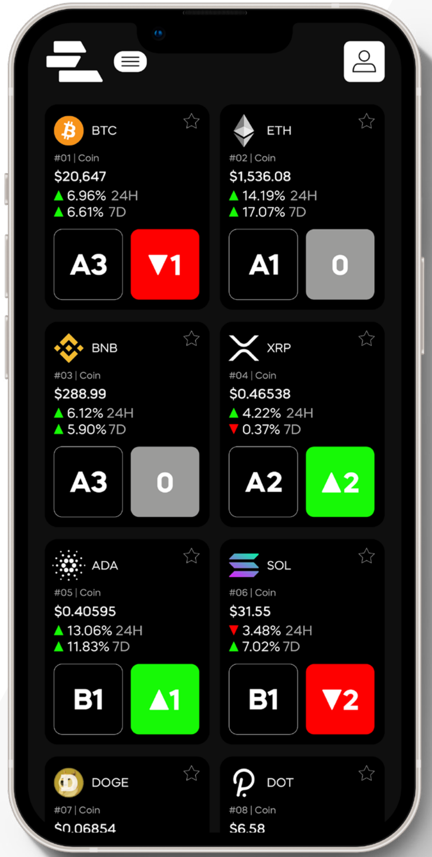
Evai Ratings
Powered by AI and machine learning

How does the Evai Market Index work?

The Evai Market Index ranks crypto assets from A1 down to D and provides an indication of the underlying value. Every week on Sunday at 01.00am GMT the Evai Market Index updates and provides investors with an unbiased guide to the market.

Users can increase potential returns and minimise risk by using the predictive power of crypto ratings to empower smart investment decisions. Let our proven ratings technology be your guide to the market.

A1 **A2** **A3**	Decreased level of risk with lower potential % returns.
B1 **B2** **B3**	Moderate risk with medium level of potential % returns.
C1 **C2** **C3**	Higher levels of potential % returns with higher levels of risk.
D	Higher levels of volatility with higher potential % returns.
U	Unrateable due to insufficient data.



How does the Evai Trading Score work?

▲3	**High**
▲2	**Medium**
▲1	**Low**
0	**No change**
▼1	**Low**
▼2	**Medium**
▼3	**High**

Plus (+) and (–) symbols will indicate the likelihood of a positive or negative price direction, while the numbers 1–3 will deliver a 1-4 hourly trading strength score relating to each asset (frequency of Trading Score will be subject the users subscription level).

The Evai Trading Score is calculated by our Multi-Factor model coupled with AI and Machine Learning to compare the daily performance of each coin with its historical data.

The following table gives the details of deciding the rating scale of cryptocurrencies according to the value of each rating criteria.

Liquidity measures

INDICATOR	VARIABLE DESCRIPTION
Turnover Ratio	Turnover ratio is the volume of cryptocurrency traded relative to the outstanding currency. The higher the turnover ratio, the more frequently the cryptocurrency is being exchanged. The easier it is to exchange, the more liquidity and consequently the higher the asset's value. The Turnover Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Adjusted Turnover Ratio	This measure is defined as the standardised turnover-adjusted number of zero-trading volume days over one month. A cryptocurrency with a higher number of zero daily volume is less likely to be traded and thus less liquid. (Liu, 2006). The Adjusted Turnover Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Amihud Ratio	Amihud Illiquidity Ratio (Amihud, 2002) represents a liquidity premium that compensates for price impact. It is measured as cryptocurrency returns relative to volume. Cryptocurrencies with high Amihud Ratio have a large price impact as buying and selling will move the price by a relatively large amount. These cryptocurrencies are considered relatively less liquid than cryptocurrencies with low Amihud ratio. The Amihud Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
FGK Ratio	The FGK Ratio is a modification of the Amihud Ratio that compares price impact against turnover rather than volume. The lower the ratio, the smaller the price impact of orders and the more valuable the cryptocurrency. It, therefore, overcomes some of the disadvantages of the Amihud Ratio, like size bias. The FGK Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.

Liquidity measures (continued)

INDICATOR	VARIABLE DESCRIPTION
Roll Spread	Roll (1984) measures the extent to which market-making will cause cryptocurrency prices to move in response to the bid-ask spread. The larger this zig-zag movement, the lower the liquidity and the more difficult to exchange cryptocurrencies at a stable price. This measure is usually used over high frequencies (intraday). The Roll Spread is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Effective Spread	This will measure the actual cost of trading as two times the spread between the bid-ask midpoint and the actual price traded. It will require information about the price at which transactions are executed as well as the bid-ask spread. The difference between the quoted and effective spread can be positive or negative, providing information about the true cost of trading. The Effective Spread is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning. Quoted Spread is the difference between the best bid and best ask price. A narrow spread implies lower trading costs and more liquidity. The Quoted Spread - or Bid/Ask Spread - is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.

Sentiment analysis

INDICATOR	VARIABLE DESCRIPTION
Fear and Greed Index	The Crypto Fear & Greed Index is evaluated as an equally weighted index of five indicators, i.e., Volatility, Market Momentum, Volume, Cap Factor and Crypto Social Media History. The indicator quantifies the simple yet important element of investing psychology, i.e., most investments happen mainly due to greed or fear, and most sell-offs similarly happen mainly due to either greed or fear. The Fear and Green Index is constructed to run from 0 to 100. A score of 100 is a top rating and a score of 0 equates to the lowest rating.
Social History Index	Evai.io understands the importance of social media ranking. The Evai.io cross-platform cryptocurrency online performance Index represents a holistic view of crypto coin performance in Facebook, Twitter, Reddit and GitHub. This index allows investors to track the specific information they need to drive their unique investing strategies. The Social Development Index is constructed to run from 0 to 100. A score of 100 is a top rating and a score of 0 equates to the lowest rating.

Volatility indicators

INDICATOR	VARIABLE DESCRIPTION
Sharpe Ratio	The Sharpe Ratio measures the return on the cryptocurrency above that of the risk-free rate, relative to the standard deviation of those returns. It is the return per unit of risk; the higher the measure, the better the investment. Sharpe (1966). The Sharpe Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.
Sortino Ratio	The Sortino Ratio also measures risk per unit of risk, but now the risk is measured as downside deviation. This is the deviation below the minimum accepted rate of return (MAR). Therefore it only combines worse-than-expected outcomes in the measure of risk. Sortino (1991, 1994). The Sortino Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.

Momentum

INDICATOR	VARIABLE DESCRIPTION
Moving Average	A Moving Average will capture the underlying trend for the cryptocurrency. It is calculated as either the simple moving average of closing prices or an exponentially weighted moving average. These can be evaluated over varying timeframes. The Closing Price relative to the Moving Average is used to evaluate ratings. Strong uptrends tend towards strong ratings and strong downtrends tend towards low ratings. Signals are to be optimised using machine learning.
Rate of Change	The Rate of Change is one of very many indicators that try to capture momentum. It is calculated as the percentage change over a specific period. The rate of change over a period of, (say) 10 days would be monitored for evidence that momentum is increasing or decreasing. It would also be compared against the price to identify divergence of price and momentum. The price relative to the Rate of Change Index are used to identify the momentum. A higher price with more momentum relates to a positive rating, while a higher price with momentum that is not moving higher signifies that the trend may be vulnerable to reversal and attracts a lower rating. Specific levels are to be optimised using machine learning.
Moving Average Convergence Divergence (MACD)	Moving Average Convergence Divergence (MACD) is a trend-following momentum indicator that shows the relationship between two moving averages of a security's price. The MACD is calculated by subtracting the 26-period exponential moving average (EMA) from the 12-period EMA. The relationship between the price and the momentum indicators determines the rating. Higher prices with momentum confirm the trend is intact. Higher prices without momentum are a warning sign that the trend may be about to change.

Capitalisation

INDICATOR	VARIABLE DESCRIPTION
Size	Size is a measure of capitalisation. There is a size factor for equities with strong evidence that firms with lower capitalisation have a relatively high return even when risk has been accounted for. Our research suggests that there is a positive size effect for cryptocurrencies with a larger capitalisation making higher returns, even when other risks have been accounted for. The rating is assessed by comparing market capitalisation across cryptocurrencies. Those with the highest capitalisation have the highest rating, and those with the lowest have the lowest rating.

Utility

INDICATOR	VARIABLE DESCRIPTION
Firm Profitability – Proxy - ROI	Return on Investment (ROI) relates net income to investments made in a cryptocurrency, better measuring cryptocurrency profitability. Measuring ROI helps in making a comparison between different cryptocurrencies in terms of profitability and asset utilisation. The level of profitability over the past year is used to assess the rating. The period to be assessed is to be optimised using machine learning.

Market Risk

INDICATOR	VARIABLE DESCRIPTION
Market Factor	The Market Factor shows the relationship between the return on a cryptocurrency and the return on a basket of cryptocurrencies. It is a measure of Systematic Risk, and it shows how much this cryptocurrency would be affected by shocks that affect the whole cryptocurrency market. This is sometimes called the beta. A beta of 1 indicates that the return on this cryptocurrency is very similar to the overall market; a beta above 1 means that the cryptocurrency is very sensitive and will react more in both positive and negative ways to changes in the cryptocurrency market; a beta below 1 shows that the reaction to the market is muted. A higher beta is considered to be higher risk. The Market Factor is compared to a moving average of past performance to assess the rating. The periods to be considered are optimised using machine learning.
Treynor Index	The Treynor Index is like the Sharpe Ratio and the Sortino Ratio as a measure of the return per unit of risk. However, in this case, the risk is measured as the Systematic Risk, the Market Risk or beta. Treynor, 1965). The Treynor Ratio is compared to a moving average of past performance to assess the rating. The periods to be considered are to be optimised using machine learning.

Overextension

INDICATOR	VARIABLE DESCRIPTION
Fibonacci retracements	Fibonacci Retracement levels can help to quantify levels of retracement risk. They are based on the Golden Ratio (0.618) and are considered levels where profit-taking or re-evaluation may naturally have taken place. The greater the retracement risk, the more vulnerable the cryptocurrency. Retrenchments across currencies are ranked and used to assess the level or retracement risk. Where the potential retracement is small, the rating will be high; where the potential retracement is high, the rating will be low.
Ichimoku Cloud	Ichimoku Cloud is part of the Japanese collection of technical tools. It is based on a combination of multiple moving averages and trading ranges and provides information about trend as well as support and resistance levels. Ichimoku Cloud produces numerous indicators that feed into the rating process. These indicators are optimised for particular cryptocurrencies and market conditions.
Bollinger Band	The Bollinger Band is one method of identifying extreme price movements. It is a trademarked property of John A. Bollinger. The Bollinger Band consists of a moving average of the price combined with upper and lower bands that are based on multiples of the standard deviation of the moving average. The bands identify price extremes, and the relative performance of the bands (converging or diverging) will help determine market conditions: consolidation or trending. They can be used to identify risk, reversal potential or the relative weight to apply to consolidation-trending tools. Bollinger Bands can identify the initiation of a trend (a positive rating if positive and a negative rating if negative). They can also show the risk of a pullback if the extreme is reached and not sustained (negative rating for a negative pullback and a positive rating for a positive pullback). Extremes and parameters are to be identified and optimised with machine learning.
Stochastic Oscillator	The Stochastic Oscillator is another momentum indicator that compares the current price to the price range over a given period. High readings show strong upward momentum and low reading strong downward momentum. The divergence between the cryptocurrency price and the momentum indicator are also used. The price relative to the Stochastic Oscillator is used to identify the momentum. A higher price with more momentum relates to a positive rating, while a higher price with a momentum that is not moving higher is a sign that the trend may be vulnerable to reversal and attracts a lower rating. Specific levels are to be optimised using machine learning.

Overextension (continued)

INDICATOR	VARIABLE DESCRIPTION
Stochastic Oscillator	The Stochastic Oscillator is another momentum indicator that compares the current price to the price range over a given period. High readings show strong upward momentum and low reading strong downward momentum. The divergence between the cryptocurrency price and the momentum indicator are also used. The price relative to the Stochastic Oscillator is used to identify the momentum. A higher price with more momentum relates to a positive rating, while a higher price with a momentum that is not moving higher is a sign that the trend may be vulnerable to reversal and attracts a lower rating. Specific levels are to be optimised using machine learning.
Relative Strength Index	The Relative Strength Index (RSI), developed by J. Welles Wilder, is a momentum oscillator that measures the speed and change of price movements. The RSI oscillates between zero and 100. Traditionally the RSI is considered overbought when above 70 and oversold when below 30. The relationship between the price and the RSI indicator determines the rating. Higher prices with the RSI above 70 confirm the trend is intact and a positive rating. Higher prices with the RSI moving lower are a warning sign that the trend may be about to change. This will reduce the rating. Levels can be optimised for particular cryptoassets and market conditions.

Bias

INDICATOR	VARIABLE DESCRIPTION
Peak End Value Demand	This is the peak return that has been achieved over the last month and the final return for the month or preceding months for the lagged version. It is a variable that seeks to capture well-known behavioural biases in decision-making related to the importance attached to peak and end experience by investors. Positive peak and end readings provide a high rating. Negative peak and end readings provide a low rating. Machine learning will be used to fine tune intermediate indications. A simple two-factor Peak-End model can explain the variations in returns between portfolios sorted by firm size and Momentum more comprehensively than popular factor models (the single-factor CAPM, the Fama-French Three-Factor Model, the Carhart Four-Factor Model, and the Fama-French Five-Factor Model). This is ground-breaking with respect to cryptocurrencies.

Advantages of machine learning and AutoML

The reason for applying Machine Learning (ML) techniques to financial data is that ML methods model non-linear relationships in the data. Non-linear techniques are required when outputs are not directly proportional to the inputs. Traditional analytical methods (e.g. OLS) assume a linear relationship, exists or utilises non-linear functions that can be simplified to a linear model. Machine Learning is a subfield of Artificial Intelligence (AI) and encompasses a large and varied set of algorithms suited to different tasks.

Here, we are concerned only with one of these categories, Supervised Learning, and the task is regression. Even so, 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. In order to make ML more accessible to non-expert users, speed up model development and deployment, automate data pre-processing and hyper-parameter tuning, and provide a performance ranking of different algorithms, Automated Machine Learning (AutoML) has been developed. AutoML is a set of algorithms that provide a unified interface to diverse ML algorithms and perform some or all of the aforementioned tasks, and more. AutoML is state-of-the-art technology still in its early evolution. There are several rival AutoML systems offered by various vendors. Commercial examples are; AutoAI in IBM Watson Studio, Google Cloud AutoML, and AutoML Microsoft Azure cloud service. There also exist several open-source versions of AutoML, such as Neural Network Intelligence, Microsoft's open-source AutoML toolkit, TransmogrifAI, end-to-end AutoML toolkit for structured data, and H2O AutoML.

For our work, it was necessary to select a specific instantiation of AutoML, and we elected to use the latter of the above, H2O Automl. We chose this because it is open-source, meaning that the source code for all of the algorithms used is in the public domain. Thus, we avoid problems inherent in using proprietary "black-box" systems. Also, it offers a selection of up-to-date ML algorithms and is among the industry leaders in the field.

H2O AutoML

H2O AutoML (LeDell and Poirier 2020) provides an interface that automates the process of training a large selection of candidate models by providing a simple wrapper function that performs several modelling-related tasks. These include; Automatic training and tuning of many models within a user-specified number or time limit. Production of Stacked Ensembles – one based on all previously trained models – are automatically trained on collections of individual models to produce highly predictive ensemble models, which, in most cases, will be the top-performing models in the AutoML Leaderboard. Several model explainer methods are provided. These apply to AutoML objects (groups of models), as well as individual models (e.g. leader model). Explanations can be generated automatically with a single function call, providing a simple interface to explore and explain the AutoML models. The H2O AutoML interface is designed to have as few parameters as possible so that all the user needs to do is point to their dataset, identify the response column and optionally specify a time constraint or limit on the number of total models trained.

The following algorithms are currently supported by AutoML; Distributed Random Forest (DRF), Extremely Randomised Trees (XRT), General Linearised Models (GLM), Gradient Boosting Machine (GBM), Deep Learning (Neural Networks), Stacked Ensembles. There follows a brief description of each algorithm.

How we Use Machine Learning

We will use the AutoML machine learning algorithm to better learn the true data generating process linking the individual predictive factors included in our models. The AutoML algorithm will train (fits) the ML algorithms we select as being most appropriate for the learning task at hand. It will also train two ensemble models, optimally combining the best performing individual ML algorithms. The trained models will be presented in a “Leaderboard,” ranked in order of performance, as determined by different statistical performance indicators. This will allow identification of the best performing model.

Also provided will be tables that allow identification of the relative importance and percentage contribution of each individual factor (independent variable) in explaining the variance of the dependent variable in the model. The Out-Comparison model of Predicted vs. Actual values also will allow us to determine whether the models we train provide a statistically significant economic advantage compared to reference linear models. Real-time adjustments are implemented to optimise weightings to maximise the accuracy of the model.

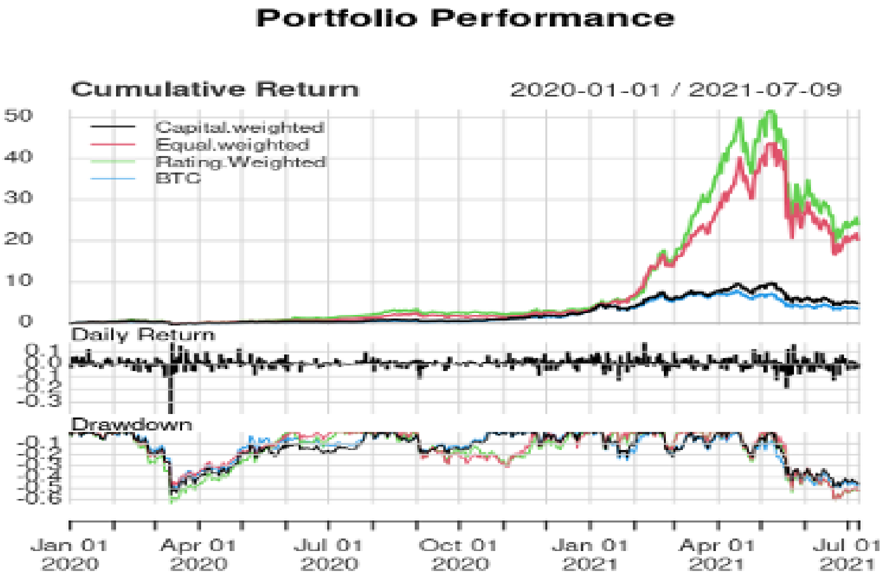
Rating Assessment

Introduction
The evai ratings are used to create a portfolio of digital assets, with the portfolio compared to a variety of benchmarks. The ratings improve the performance of the portfolio relative to the benchmarks outside of specific cases. The results are robust to alternative benchmark specifications, alternative time periods and alternative risk measurements. There is strong evidence that Evai ratings can improve investment performance.

Results
The table below shows annualised returns, annualised volatility and the Sharpe Ratio, return per unit of risk, for the rating-based portfolio and a number of benchmarks.

The rating-based portfolio has the highest return of the benchmarks against which it is tested. This provides a compensation for the increased risk. The return per unit of risk, as measured by the Sharpe-Ratio, is more-or-less the same as that for the equally-weighted portfolio.

The table reports a number of daily performance metrics for the four portfolios over the period from the beginning of 2020 to mid-July. The advantage of the diversified portfolio of cryptoassets is clear from the performance of rating-weighted and equally-weighted portfolios. BTC has a weight of 60% in the weighted capitalisation portfolio.



The worst day for the rating-weighted portfolio was 12 March 2020 when the fund lost 43% of its value. There is a lot of risk in crypto and the rating-based portfolio does not seem to avoid this. The portfolio suffered the maximum drawdown, the greatest 5% VaR and some negative skew. These metrics would have been improved if the SAND coin was incorporated into the portfolio. SAND was removed as an outlier as a consequence of the 4000 percent increase experienced on 14 August 2020.

The portfolios

- The rating-based portfolio is based on weights calculated according to the ratings at the beginning of 2020.

  The weight for each coin is determined by: $weight_i = \frac{RT_i}{\sum_{i=1}^{i=N} R\,T_i}$

  where RTi is the ten scale rating for the ith currency where A3 = 1 and U = 10.

- The equally weighted portfolio weights all coins equally.
- The capitalisation-weighted portfolio weights coins according to the capitalisation at the beginning of 2020.

  The weight for each coin is determined by: $weight_i = \frac{CP_i}{\sum_{i=1}^{i=N} C\,P_i}$

  where CPi is the capitalisation of the ith currency. Coins without capitalisation data at the beginning of 2020 are excluded.

- BTC is also used as a benchmark of performance.

Extensions

Additional testing needs to be done with alternative specifications. These will include:

- A more dynamic weighting process that will assess performance when portfolios are rebalanced once per year.

- An adjustment of the weighting mechanism that will increase the importance of the rating system, boosting the highly rated currencies and reducing the weight of the low rated currencies.

- At the moment there are 39 currencies being assessed over a two year period. The results do not change significantly when the portfolios are assessed over the period 2017 to the present day. They do not change significantly when SAND is included. For the current study SAND was excluded as it had a near 4000 percent increase in value on 14 August 2020 when it began trading on Binance. With SAND, the rating-based portfolio has a more positive risk profile with a positive skew to the distribution of returns.

- Creation of smart beta portfolios. A momentum portfolio, based on those coins with the best performance over the last 6 to 12 months; a minimum-variance portfolio, based on those portfolios with the lowest variance over the last 6 to 12 months. If some validation metrics can be discovered, growth and value portfolios can be created.

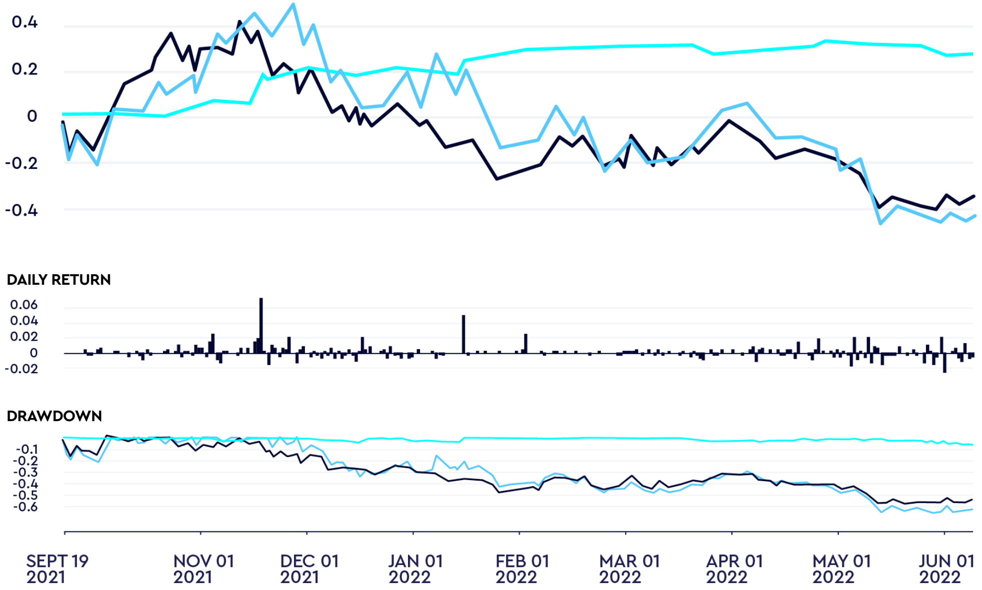
- Long-short portfolios can be created. For example, the portfolio could be long 50% based highest rating and short 50% based on the lowest rating. It is also possible to have a 130% long, 30% short strategy to maintain market neutrality. These will depend on the cost of shorting.

- It is also possible to examine a correlation matrix of the returns of these 38 coins for the period since the beginning of 2020.

Evai ratings performance - proof of concept

From September 2021 to June 2022 our research shows that a trading strategy based on Evai's ratings outperforms a passive Bitcoin investment strategy and buy-and-hold strategy on the same portfolio of crypto assets. The Evai strategy also demonstrated its ability to outperform the S&P Equity Index and Gold over the same investment period.

CUMULATIVE RETURN



	EVAI	Equal	BTC	Gold	SPY
Return	**25.4%**	-42.8%	-34.5%	6.8%	-5.0%
Standard Dev	**13.8%**	67.1%	55.7%	13.7%	20.8%
Sharpe Ratio	**1.83**	-0.63	-0.62	0.50	-0.24
Daily Max	**7.4%**	18.2%	14.5%	2.7%	3.0%
Daily Min	**-2.6%**	-14.4%	-11.6%	-3.0%	-4.0%
Max Draw Down	**5.6%**	65.5%	57.6%	11.8%	18.2%

Strategy and investment portfolio

The crypto assets used in this assessment are: BTC, ETH, SOL, ADA, BOMB, BORA, DOT, HNT, JUP, MATH, MONA, QTUM and SALT. The investment strategy deployed, focused on trading activity around 3 unit increases/decreases in the Evai rating.

The approach used 5 buy signals and 4 sell signals in the 9 month period. By the end of the cycle, the strategy included a long position in BTC, SALT, BOMB, MONA and BORA with short positions for ADA, DOT and JUP. The long position in JUP has a very large effect on the performance around the turn of the year.

During the research period, the strategy deployed equal amounts of money in each crypto asset. Therefore, the size of the investment increased with the number of positions. An alternative approach would have been to spread a set investment across all the positions. Taking this approach in future would improve performance of the portfolio by increasing the size of one winning position.

EVAI STRATEGY
EQUAL WEIGHT
BTC BUY & HOLD

Leadership Team

Matt Dixon
CEO and Founder of Evai.io

Professor Andros Gregoriou
Chief Research Officer

Igor Arkhypenko
Chief Technology Officer

Arif Al Otaibi
Chief Strategy Officer

Dr Marwan Alzarouni
Co-founder/strategic advisor

Preeya Patel
Head of Business Development

Marsela Tafa
Ratings Director

Prof. Guy Liu
Research Director

Dr. Rob Hayward
Ratings Analyst

Nick Hamilton
Marketing & Comms Consultant

Evai Tokenomics

CURRENT PRICE: **$0.012**

PROTOCOL: **BINANCE SMART CHAIN (BSC)**

SYMBOL: **EV**

DATE OF LISTING: **April 2022**

CIRCULATING SUPPLY: **22,046,452**

MAX SUPPLY: **1,000,000,000**

TOTAL SUPPLY: **799,909,593**

FULLY DILUTED MARKET CAP: **$9,598,915**

CURRENT MARKET CAP: **$264,557**

Funding & Reserves

FOUNDATIONAL RESERVE	**68%**
OTC SALES	**10%**
SEED SALE	**5%**
PRIVATE SALE	**3%**
PUBLIC SALE	**14%**

Allocation of Funds

OPERATIONS	**20%**
LISTING & LIQUIDITY	**20%**
LEGAL	**5%**
DEVELOPMENT	**35%**
MARKETING	**20%**

Equity Allocation

EQUITY ALLOCATED	**93%**
EQUITY AVAILABLE	**7%**

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