Hybrid Intelligence for Effective Asset Management

White Paper

Authors (Cindicator team):

Mike Brusov, Chief Executive Officer and Co-founder
Yuri Lobyntsev, Chief Technology Officer and Co-founder
Kate Kurbanova, Head of Analytics
Nodari Kolmakhidze, Chief Investment Officer

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Abstract

Cindicator creates the social and technological infrastructure needed to make effective decisions under the volatile conditions of the new economy.

By combining a large number of diverse financial analysts and a set of machine-learning models into a single system, we are developing a Hybrid Intelligence infrastructure for the efficient management of investors' capital in traditional financial and crypto-markets.

The benefits of Hybrid Intelligence for an ecosystem and community are:

- a technological and analytical infrastructure for the efficient and safe management of investors' capital by investors themselves or licensed managers;
- an opportunity for analysts to monetise their intellectual assets without risking their own funds;
- tools and data for making investment decisions under the conditions of market uncertainty;
- up-to-date analytics of the industry, expectations, opportunities, and market growth points;
- indices and ratings of crypto-assets.

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1 Introduction to Hybrid Intelligence

1.1 What is Hybrid Intelligence?

Hybrid Intelligence is the combination of human intelligence and machine intelligence, and their interaction in resolving various tasks. One sort of intelligence supplements and strengthens the other.

Clearly, one may face many challenges during the decision-making process. Hybrid Intelligence and other related systems under development are appropriate for resolving these kinds of difficulties. This is not only due to the criterion of speed in decision-making - namely, the question of why one should waste time on simple tasks that can be resolved by both individuals and simple mathematical methods and algorithms? It is also related to the complexity of the tasks and the level of uncertainty in the systems used to resolve them.

In one of his latest interviews - Elon Musk speculates that humans should soon merge with artificial intelligence and create a new kind of interface. This symbiosis could help people settle one of the most complex tasks facing mankind: predicting the future with high accuracy.

People have long tried to resolve this issue in all areas of business by using various technologies with varying degrees of success. Investors and traders try to predict future share prices or company success to increase the profitability of investment deals. Political analysts try to predict the results of presidential elections, while corporations put a great deal of resources into attempts to foresee future technological trends. Many of them have already used intellectual crowdsourcing to undertake these tasks to a greater or lesser extent. Let's take a look at the existing solutions.

1.2 Areas of application

1.2.1 Venture investments

Most investment venture deals are closed by "syndicates" at the moment. This means that several investors take part in one round of the deal at the same time. This trend has been increasing year on year. In addition to syndicate deals - which involve partner venture funds - specific associations and collective investment clubs emerge each year (Angel-List is the most famous example).

Why do venture (and other) investors prefer group deals rather than individual ones, despite the fact that sharing a profitable investment with one's competitors seems to make no sense?

One of the reasons for such deal structures lies in the use of collective intelligence systems for risk hedging against the potential mistakes of group thinking. This could happen when an investor makes the wrong decision about a deal based on a false insight, trend, or insufficient competence in a given area. In a syndicate, a set of competencies and the investors' previous experience can be very different, which allows them to view the startup as a whole, as well as looking at the team and the potential risks from various angles and to cancel the deal if there are sound reasons to do so. For most venture investments, the best deal is a deal that has never been done before.

Now imagine the collective intelligence of professional investors combined with artificial intelligence technology, which, based on the use of a large volumes of data in real time (including the number of exits, the stock market situation in a specific area, the state of the labour market, and even the behaviour of startup founders on social networks), adapts to current market conditions and produces signals for entry or non-entry into a deal, free from emotional factors. Most investors at the pre-seed and seed stages admit that emotions are still the main drivers in investment decisions.

1.2.2 Science

The symbiosis of these two types of intelligence could, in this case, efficiently downplay the disadvantages of human 'emotional' approaches by strengthening the decision-making signal with a number of decentralised data analysis points. Using such a method is reasonable in systems with higher uncertainty and highly complex of tasks, for example in biotechnologies. In a renowned scientific paper, researchers created a game in which each player with a different degree of knowledge could take part in molecular docking (a process that helps predict the structure of a future chemical element with certain desired properties). Each project participant could bind a molecule of the protein together in any way. Using this crowdsourced data from a variety of experts combined with virtual screening (computer modeling and machine learning) enables scientists to create new medicines by combining a molecule (medicine) with a target protein (cancer target). The synergy of the two types of intelligence allows humanity to invent medicines for diseases that were once incurable.

In 1906, the famous British scientist Francis Galton came to a rural fair where visitors were invited to guess the weight of a bull put on public display and to write the figure on a special ticket, supposedly just for fun. The organizers of that show promised prizes for those who managed to guess the correct figure. Thus, about 800 people, some of them inveterate farmers, and others far from pastoral affairs, took part in the voting. After collecting all the tickets for analysis after the fair, Galton calculated the average arithmetic value from the entire sample: 1197 pounds. The actual weight of the bull was 1198 pounds. This means that as a group, the people gave an answer incredibly close to the true figure.

As evidenced by statistics from the Who Wants To Be a Millionaire? television game show, after contestants used the Phone-a-Friend option to phone an erudite friend, a correct answer was chosen in only 65% of cases, but when the player requested audience assistance, the aggregate answer from the audience was true in 91% of cases.

Such studies of the wisdom of crowds were used widely amid the boom of studies dedicated to group dynamics between the 1920s and 1960s. The sociologist Heigl Knight, for example, asked students to estimate the temperature in the room. The arithmetic average of the group's opinions estimated the temperature in the room at some 22.44 °C, while the actual temperature was 22.2 °C.

1.2.3 Corporations and businesses

Google, Johnson & Johnson, and many other large corporations use 'collective intelligence' for new corporate management technologies. Corporations have already begun to integrate the technology of idea crowdsourcing and future forecasting into their strategic processes to crowdsource new ideas and generate forecasts for the future of the company and its competitors (sales plans, new product releases, or entry into new markets).

Top management collects proposals and signals from various employees and departments (on a decentralised basis, which is important), such as points of view and 'insights' from sales managers, who collect market feedback on a daily basis, as well as developers, who possess information on the actual value of technologies and the company's fulfilment of its product plan, which are completely different in nature and value. Combining this system with the unbiased algorithms of big data processing (on sales data, analytical reports and forecasts, and the constantly changing market situation) and mathematical modeling, top management gains access to an extremely valuable decentralised source of decision-making, which can be used in combination with other strategic parameters.

1.2.4 Politics

Certainly, a similar technology can be used for political purposes. A noteworthy case is a well-known student project launched in 1988, the Iowa Electronic Market. It turned out to be one of the most precise tools for predicting the results of political events and elections for most countries around the world. Participants in this 'market' can buy or sell contracts for the various results of future political events (similar to short and long positions on the stock exchange), thus forming expectations and determining the exact probability of victory for one or another presidential candidate. For two decades, this technology has been predicting the results of US presidential elections with great precision, when compared with any analyst or company (until the most recent election incidentally).

1.3 Hybrid Intelligence for investments and asset management

Undoubtedly, stock exchanges are still the leaders in researching and using Hybrid Intelligence in business - this is an area where traders have to make decisions on millions of dollars every second (and trading robots do so every millisecond).

Financial markets themselves are the daily prediction of the future in its pure form. At what price and when is the best time to buy Facebook shares, Brent crude oil, the US dollar, or Bitcoin? All these questions are the subject of daily predictions of traders and analysts.

Major current market analytics related, for example, to forecasting the future in terms of finances are created by a limited number of professionals using roughly the same information. Each year the pace of information retrievals accelerates and the value of such reports falls, with fewer and fewer professional traders reading them or taking them seriously.

Nonetheless, such analytical reports bring in an impressive amount of money all over the world. In 2015 alone, professional traders spent over $50 billion purchasing financial market data, of which $4 billion was spent on professional analytical services and systems (predictive analytics). By 2020 this figure will increase approximately six times. And these are only professional analytical systems. The B2C financial information market for non-professionals is huge: for example, 54% of US residents have bought shares at least once in their lives, and in China about 30% of residents are engaged in stock trading.

Recognising the potential and size of this market, we decided to put the technology of Hybrid Intelligence to good use in financial markets as a top priority.

2 Ecosystem of Hybrid Intelligence

Thousands of analysts on the Cindicator platform generate various forecasts daily, answering a number of specific questions about the price levels of different financial assets, macroeconomic indices, and events significantly influencing the market.

Examples:

- create a forecast of the minimum and maximum price levels of Bitcoin for the coming seven-day period;
- will the Tesla stock price surge to $345 during market hours on Friday?;
- will the U.S. unemployment rate be greater than or equal to 4.5%, according to the 2 June report?;

- will Bancor collect more than 100 million during the first week of ICO?;
- what is the probability of Trump's impeachment during the next three months?

Cindicator works by using a large dataset that is transferred to a mathematical block consisting of a machine learning model ensemble (cleaning, clustering methods, linear regressions, Bayesian models, xgboost on decision trees, genetic algorithms, and neural networks). Machine learning models dynamically calculate various weightings for each forecaster, identify stable systematics in their errors and calculate corrections for the errors, eliminate noise, and generate final predictions and trading signals.

At the core of our Hybrid Intelligence system is the synergy of the collective intelligence of a large group of dissimilar decentralised analysts combined with artificial intelligence (machine learning, and a self-learning model based on a variety of dynamic feedbacks).

Let's review these two ecosystem framework components in greater detail.

2.1 Collective intelligence

In order to ensure effective operations, any group intelligence system should meet the following criteria.

The complexity of every goal set.

For results to have any relevance, they cannot be derived from extremely complicated questions addressed to different users (i.e., the expected Bitcoin price in USD in 376 days). However, the collected signal should present sufficient value. Aside from the complexity of the set task/issue, there is a need to create the most convenient infrastructure for each participant to make such forecasts. To do so, in December 2015 we launched a mobile platform where we focused on the interface used by forecasters. As a result, it takes three to five minutes for each user to generate one data point.

Group diversity and decentralization.

Members of a single group intelligence should possess varied knowledge and competencies, intelligence, personal experience, and views. If a particular segment prevails in a group, the system will be incapable of generating an accurate signal in the event of an incorrect insight.

A group may have a lot of outliers, errors, or subjectivity; however, the diversity and multidirectionality of these points allows them to be ignored in modulus (the simplest example is the Gaussian distribution).

Furthermore, the group should be completely decentralised. No communication or exchange of opinions inside the group is allowed in order to avoid the influence of some individuals on others.

Motivation of each group member.

Each group intelligence member must be highly motivated to generate the most accurate forecast possible (according to current knowledge and possibilities).

We have developed multi-level motivation for our platform, based on important aspects of human psychology.

Financial motivation.

Each month, we distribute funds proportionately to each user's ranking in the application. The more accurate the forecasts a user makes, the more compensation they receive. Erroneous forecasts, and low activity downgrade the rankings. Accordingly, each user's compensation depends on their personal activities and the accuracy of the forecasts.

Competitive motivation.

We have developed internal user rankings, special nominations, and other gamification elements to enhance the competition factor.

Involvement with trades and investment.

On our platform, users do not merely forecast in order to maximise their points; each forecast is a micro-involvement of every user in a real or simulated trading transaction or investment. Our trading robots complete a real or model trade linked to every question posed. This is a significantly promotion of the involvement of every participant, both individuals and the group as a whole, and increases responsibility.

Training.

Getting daily feedback on the accuracy of their forecasts as well as increasing their level of knowledge before preparing each prediction helps forecasters to enhance their skills and find the best strategies for forecasting various types of events.

2.2 Artificial intelligence

The artificial intelligence system is only the first stage which generates a large amount of 'raw' data. Next, Cindicator's 'black box' is used, with the following core elements:

(1) the system and methods defining the confidence weight (with constant adjustments after each question and trade) for each user, which takes into account:

- the personal track record of each member's accuracy, divided into clusters (signal types, instrument types, links between answers, etc.);
- dynamic feedback following each trade with regard to the value (profit or loss) of each user's forecast;
- the predictive model, which (in a very short time) is capable of defining superforecasters in the group.

(2) trading strategies and models to seek the best possible way of using the enriched data to create trading robots:

- testing of various trading strategies and hypotheses;
- constant backtests and forward tests to adapt the models to the constantly changing market environment.

3 Token sale

By releasing CND infrastructure tokens, we offer all participants (traders, investors, forecasters, analysts, data scientists, and the Cindicator team) the chance to become the creators of a decentralised ecosystem of Hybrid Intelligence for more efficient asset management.

Each CND token holder can obtain a new level of access to Cindicator's indicators, indices, data, services, information, and analytical products. The level of access and the products and tools available will depend on the quantity of tokens in each holder's possession, which will in turn be influenced by each token holder's role and active participation in the decentralised ecosystem.

We also plan to place CND tokens on exchanges, giving people the opportunity to buy them openly (for residents of countries where the purchase of tokens does not violate local laws), gain access to new products, or sell them to interested traders, analysts, or investment funds. Tokens cannot be sold to residents of the USA, Singapore, PRC, or other countries where the sale of tokens may require registration as a security.

Legislation on the circulation of securities in certain countries, such as the USA, Singapore and PRC prohibits the sale of CND tokens to the residents of those countries. When you buy CND tokens, you should be aware of the restrictions on their subsequent sale and promise to follow our instructions and/or those of the exchange when reselling them to other users.

3.1 Expediency of issuing CND tokens

The issuance of our own infrastructure tokens is conditioned by the need to create an internal economy in the ecosystem that will establish transparent and fair relations among all participants comprising the system: forecasters and analysts, traders, financial investors, data scientists, and the Cindicator team.

3.1.1 Effective economic motivation of all ecosystem participants

Blockchain, decentralization, and a fair system of economic motivation are ideologically and systematically integrated into the structure of the predictive product module. Their purpose is to create a system of long-term motivation that encourages forecasters to perform their intellectual work better, thereby increasing the effectiveness of the entire technology and its benefits to the community.

To ensure more efficient and fair motivation for active participants of the ecosystem, (forecasters currently, but also data scientists and traders in the future) we will locate direct causality between the quality of their engagement and the result of real or simulated trading transactions or investments (which are based on participants' forecasts, intellectual work, data processing models and trading strategies).

For this reason, after the crowdsale and acquisition of the necessary licenses, we will allocate part of the funding to the trading portfolio (managed by Hybrid Intelligence). Potential profit from this portfolio will be used to replenish the dynamic motivational ETH/BTC pool to reward forecasters (in proportion to their rating, accuracy, and participation over a given period). Therefore, financial compensation for active ecosystem participants will be directly linked to the trading module performance. This compensation is designed to be a reward mechanism incentive for accurate information and forecasts provided and contributed to the system and is not applied to CND holders generally.

3.1.2 Necessity to business

Throughout 2016 and early 2017, we launched test integration with hedge funds and banks to monetise our technology by providing them with products and APIs. We identified the poor scalability of this classic B2B model—large funds wanted to monopolise our technology, data, and trading signals (primarily because of the limited market capacity — funds with the same valuable alpha began to compete in utilising these signals). In other words, we realised that selling our solution to a large number of B2B customers would be unwise from a business point of view.

The issuing of infrastructure tokens is the next step towards the creation of technological infrastructure (API + forecasting module + data science module + trading module + GUI module), which will be used by investment funds working under the new format for utilising all products and capacities of Hybrid Intelligence with maximum efficiency.

Funds that would purchase this technology will be regularly paying the performance fee from their potential profit, to the extent of which the dynamic motivational ETH/BTC pool will be replenished in order to increase the motivation of all active participants of the ecosystem (forecasters , traders, data-scientists). This infrastructure is scheduled to be available for funds in 2019.

In order to preserve maximum efficiency in the utilisation our technology by investment funds (hedge funds, crypto asset funds, venture capital funds) access to this infrastructure will be granted only for those who own a significant number of CND tokens.

3.2 Terms of token sale

3.2.1 Terms of issue of CND tokens

CND tokens will be issued on Ethereum blockchain using the ERC20 token standard.

Token sale period: 12 September to 12 October.

Prior to the crowdsale, we plan to start selling the tokens via the White List in several iterations. There is a possibility that all tokens will be sold through these stages before the start of the crowdsale.

100% of the tokens will be issued within the token sale period.

Purchase methods accepted: ETH.

Price of 1 CND = $0.01 (fiat price equivalent provided for illustrative purposes only, no fiat currency will be accepted).

Maximum hard cap = $15,000,000.

3.2.2 CND token distribution

Tokens will be distributed as follows:

75% – for token sale contributors;

20% – for the Cindicator company (+ vesting);

3.8% – for advisors and partners;

1% – for the bounty campaign;

0.2% – for current Cindicator forecasters (proportionally to their total rating).

3.2.3 Funding allocation

Funds will be allocated as follows (proportions below are not final and may change at company's discretion based on business needs):

55% - budget for continuation of scientific work, infrastructure development, creation of new products, development of a Hybrid Intelligence platform. The budget will be allocated between these areas as set out below:

- development: data science, machine learning, AI modules, mobile applications, web versions, products, API, web-hosting, server capacity;
- trading: trading services and terminals, development of trading algorithms and infrastructure;
- operational costs: salaries, office rent, other operational costs.

20% – Hybrid Intelligence portfolio for technology validation, the accumulation of valid trading data and formation of a dynamic motivational ETH/BTC pool for forecasters. The trading cases of this portfolio will also serve to make up a history of transactions, which will contribute to growing interest and demand for Cindicator products in the professional market of investors and traders.

10% – marketing: promotion of the collective intelligence platform in order to achieve significant growth in forecaster numbers.

5% – legal support, improvement of company's legal structure, protection of investors' rights.

5% – monthly forecaster compensation fund.

5% – acquisitions and future partnerships for the synergetic development of the Hybrid Intelligence ecosystem.

4 An economic model for the ecosystem

4.1 Products for CND token holders

By buying tokens, CND token holders will get exclusive access to part of the Hybrid Intelligence infrastructure (currently under development).

Holders of the CND infrastructure tokens will receive a different level of access to Cindicator's indicators, ratings, and internal analytical products.

Token holders will be able to access the following parts of the infrastructure:

- indicators of traditional markets and crypto-markets (the probability of the rise or fall of asset prices, the probability of beating consensus in corporate and macroeconomic events, indicators of certain price levels being reached, and indicators of the probability of significant events influencing the market);
- auxiliary service products for trading (Telegram and Slack bots, notifiers, and portfolio monitoring products);
- analytical products (ICO ratings, market condition analysis, ICO due diligence, and investor portfolio analysis);
- market indexes and sentiments generated by Hybrid Intelligence.

The fact that token holders can use data from the analytical infrastructure products will not affect the value of the data received from Hybrid Intelligence, since each indicator or index is not an unambiguous trading signal, but only an additional metric in the market that helps to analyse an investment decision. These data and analytical products will assist token holders and make the ecosystem transparent.

However, a part of the infrastructure intended to be directly used in capital management (by traders' teams, machine learning models, and trading strategies) will remain in the centralised part of the system. This is necessary in order to make sure that Hybrid Intelligence can be used most efficiently at the next stage, when interested funds will be provided with access to the entire infrastructure (see Section 4.6).

4.2 Limited access to products

To prevent the dilution of analytical data value (taking into account market capacity and the potential impact on it), the access level and set of available products and tools will be set for CND tokens.

Part of the products will just be made available to the token holders in accordance with their balance level, and part of the products will be sold through transfer of tokens to the dynamic motivational CND pool.

Exact formation of the access levels will depend on the crowdsdale results (number of the tokens issued) and the market dynamics, and will be determined by the appropriateness thereof for Cindicator's internal economy.

We will deliver these products in various ways once the corresponding development work is complete:

- Daily/weekly/monthly distribution of indicators via messenger/email;
- SaaS(Software as a Service) — a dashboard with an access to indicators and analytics of Hybrid Intelligence for various events;
- Mobile application;
- API access.

4.3 Trading portfolio of Hybrid Intelligence

In order to validate the RD progress on to develop the Hybrid Intelligence technology, and to verify the quality of the Cindicator analytical products, a Hybrid Intelligence Portfolio will be created.

This Portfolio will be divided into the three parts, in order to cover the most promising and scalable trading strategies, as well as for effective risk hedging:

1. Active cryptotrading based on Cindicator technologies, along with data and signals retrieved from the consensus of Hybrid Intelligence. This portion of the portfolio will vary with cryptomarket liquidity. At the moment, liquidity makes it possible to comfortably use a small percentage of the total portfolio in active strategies. Bitcoin will be used as a benchmark to estimate the results.
2. Protective buy and hold portfolio of crypto assets (the proportion of various assets in the portfolio is determined by consensus). The task of Hybrid Intelligence is to determine the optimum ratio of crypto assets from the viewpoint of risk minimisation, and to keep this ratio up to date. Bitcoin will be used as a benchmark to estimate the results.
3. Active trading of traditional financial assets: stocks, futures, and foreign exchange markets on the basis of Cindicator technologies, as well as data and signals retrieved from the consensus of Hybrid Intelligence. This part of the portfolio is used to demonstrate the capabilities of Hybrid Intelligence in traditional markets. It can also be treated as protective in relation to the entire cryptoportfolio. In the case of a strong fall in the cryptomarket, a portion of the funds may be transferred to cryptoassets with the purpose of earning a profit upon the rehabilitation of that market. USD will be used as a benchmark to estimate the results.

Active management of the third part of the portfolio will begin within a few months after the end of the Token Sale. To do this, we will need to complete the preparation of the entire trading infrastructure, such as accounts and legal structure (it is necessary to establish a separate legal entity for the fund and to obtain the necessary licenses).

This portfolio will be managed by our team of traders and trading robots, who will use the data, signals, and analytics obtained through the Hybrid Intelligence technology. We will apply various strategies in the financial markets (both crypto and traditional) within different time horizons, from short-term trades to long-term investments. The choice of strategy and assets invested will draw on a positive evaluation from Hybrid Intelligence, as well as successful testing in the form of back and forward tests.

Our team will prepare detailed monthly reports featuring the results of the trades executed and make them available to the community.

4.4 CND pool for dynamic compensation of forecasters

To form a steadily growing internal economy, Cindicator will create the internal motivational pool of CND tokens.

The pool tokens will be used to encourage the Cindicator forecasters, as well as other contributors to the ecosystem, who will be bringing significant values to the ecosystem of Hybrid Intelligence (scientists, visionaries, engineers, traders, investors, marketers, vendors, etc.).

For the contributors to be encouraged, CND pool tokens will be brought to the pool primarily from selling of the Cindicator analytical products - those products and technologies that will be available only through the sale of CND tokens by Cindicator company.

4.5 ETH/BTC pool for dynamic compensation of forecasters

Every quarter we will record the results of all the accounts in the Hybrid Intelligence portfolio in order to form a dynamic motivational ETH/BTC pool, designated to reward forecasters for their intellectual investment into the ecosystem.

In the case of positive performance (relative to the initial state of the portfolio), we will distribute the profit as follows:

1. X% will remain in the Hybrid Intelligence portfolio, ensuring its growth for the next reporting period;
2. Y% is the performance fee for the Cindicator team (to be paid only if the portfolio size is larger than its initial state);
3. Z% - funds to replenish the dynamic motivational ETH/BTC pool.

In case of a loss, we will can use the reserve fund to provide financial motivation and compensation to the superforecasters for the period in question.

The parties acknowledge that the current state of the cryptocurrency industry is uncertain due to fast changing regulations and/or lack of regulatory certainty in several jurisdictions. To comply with any regulations and/or to ensure viability of its business model in light of any market, technological, and/or regulatory changes, Company reserves the right to amend, supplement, or delete any term of this Agreement, including but not limited to any terms dealing with the creation of dynamic motivational pools.

4.6 Monetisation of intellectual contribution of forecasters

Forecasters forming the Cindicator collective intelligence are the key element to be created with in the ecosystem. The successful operation of this system as a whole requires the personal motivation of forecasters to be sustained, and a common goal to be formulated for the entire group.

Our platform enables professional and non-professional analysts to monetize their intellectual work in analysing markets and generating predictions. We call this product the Collective Intelligence Platform, in which our forecasters can invest their mental asset (time, attention, intelligence) and be eligible for the respective compensation of their embedded intellectual investments, with no risk of losing their own financial assets.

Personal motivation

Each forecaster generating various forecasts in our application is given a personal rating, based on the forecasts' accuracy. The rating may both increase and decrease, depending on the accuracy of each prediction. The rating of each forecaster is made public, which creates the necessary competitive motivation for each of forecaster.

At the end of each month the rating is fixed, and the most accurate of forecasters in the ratings share the cash prize in proportion to the number of points accrued that month. The monthly cash prize is formed from the reserve fund of forecasters' remuneration and depends on the number of forecasters at the time. The size of the monthly prize and the rules for its allocation are announced before the start of each month.

In the beginning of each month, this rating is reset (in order for everyone to have an equal chance in the new period) and a new monthly stage begins.

Group motivation

The overall goal of the entire forecaster group will be related to the result of trading the Hybrid Intelligence portfolio, since they are an integral part of its management.

At the end of each reporting period (quarter) we will record the results of trading of the Hybrid Intelligence portfolio (for the traditional portfolio in USD; for the crypto-portfolio in BTC). In the case of profit generated on any of the accounts (according to the corresponding benchmark), one part thereof will be applied into the dynamic motivational ETH/BTC pool for allocation between the forecasters, as the additional bonus in proportion to their rating in such reporting period.

In case of a loss on both accounts, no additional bonus will be provided to the forecasters.

4.7 Technological infrastructure for investment funds

The final goal is to create a complete infrastructure for the new generation investment funds which will buy access to Cindicator technology (API, forecasting module, data science module, trading module, GUI module, security system).

The funds will be able to access this technology by buying necessary (see section 4.2) amount of CND tokens. Funds that would purchase this technology will be regularly paying the performance fee from their potential profit, to the extent of which the dynamic motivational ETH/BTC pool will be replenished in order to increase the motivation of all active participants of the ecosystem (forecasters , traders, data-scientists).

The number of funds that will get access to the full infrastructure will be limited in order to maximise the efficiency of the infrastructure on each market (cryptoassets market, traditional stock market, currencies market, derivatives market, venture capital market).

This will provide an efficient supplement to Cindicator's ecosystem, increasing its sustainability and providing benefits for all active members.

5 Technologies applied

5.1 Technological infrastructure

The Cindicator technological infrastructure is already developed at the time of the token sale and consists of the following modules.

Business logic module:

- Backend system with basic business logic that works with events;
- Administrative system;
- Viewing data and indicators;
- Mobile applications (iOS + Android);
- Web application (under development).

Prediction module:

- Data acquisition;
- Filtration and cleaning of acquired data;
- Feature extraction;
- Forming of hypotheses and mathematical models;
- Validation and optimisation of parameters for predictive models;
- Synthesis of accurate predictions.

Trading module:

- Data acquisition from the predictive module;
- Integration with exchanges, acquisition and processing of resulting data;
- Back tests and forward tests for parameters of trading strategies;
- Implementation of trading strategies through trading robots.

5.2 Data science and machine learning (ML)

ML is employed by Cindicator to accurately forecast the actual behaviour of financial instruments based on data from the market and forecasters' predictions.

To achieve this goal, two major approaches are used: superforecasting and the wisdom of the crowd.

We undertake this work in several ways:

1. We study our forecasters, identifying behavioural patterns and common factors.
    - We cluster forecasters: into bears or bulls, those who narrow or expand price levels, analyse the market or not, follow the trend or not, use technical or fundamental analysis etc;
    - We explore behavioural patterns: how often forecasters make mistakes, in which situations they are mistaken, and how forecasters react to a dramatic change in the market and different economic events.
2. We conduct experiments with groups and clusters.
3. We conduct experiments with predictive models and use them to build the boosting algorithm.
4. We conduct time series analysis of the market and the predictions of forecasters.
5. We validate machine learning models and optimise their parameters.

5.3 Description of current pipeline

Data available:

- Forecaster profile (gender, age, country, professional background, occupation, and behavioural patterns);
- Forecasters' predictions for different financial assets (binary questions, price-related questions);
- Historical market data on various financial assets.

We use the classical pipeline of machine learning models.

5.3.1 Data filtration and clean-up (data preparation)

The main source of random errors is forecaster input errors (where the user indicated the wrong ticker symbol or specified an incorrect number order). These errors adversely affect the work of models and displace our metrics. For data clean-up we use the following methods: IQR, Grubbs Test, and GESD.

5.3.2 Feature extraction

Each forecaster and investment instrument has a distinctive behavioural pattern. Our algorithms consider these patterns and apply either charge different weightings or different models in the appropriate manner. We have developed a model that constantly updates the feature vector and recalculates its weightings based on RL (reinforcement learning).

5.3.3 Construction of hypotheses and mathematical models

All our models can be divided into two classes:

- Superforecasting models (in which we build models on various forecasters' clusters and cluster ensembles);
- The wisdom of the crowd model (in which we build various models on the predictions of all forecasters).

We develop mathematical models for description and prediction based on the theories of phase transitions and game theory. We also use fractal geometry to forecast critical points (points where the market experiences increased tension, when the topological dimension and the Hausdorff Dimension are changing dramatically).

5.3.4 Validation and streamlining of predictive models

Our models are optimised and back test-assisted due to the pipelines involved. Different models demonstrate their own specific behaviors for different investment instruments. Each model has its own settings (the length of the sliding window, the form of the function for calculating weights or penalties, the depth of the decision tree, and others). Tuning of parameters is done for each model with regards to each financial asset. Each model is constantly learning on the basis of new data. To assess the accuracy and quality of our models, we perform back-testing and use both standard scores (RMSE, ROC, MAE, Pearson's correlation coefficient) and their intrinsic evaluation functions for each trading strategy.

5.4 Description of validated hypotheses and approaches

5.4.1 Confirmation of correlation between analysts' forecasts and real market behavior

To demonstrate existence of strong correlation between analysts predictions and real market behaviour, we turn to the basic mathematical statistics.

Let R^2 – be the coefficient of determination, one of the general mathematical metrics, which determines the degree of correlation between the data. It is believed that, when the condition $R^2 > 0.5$ is satisfied, there is a strong correlation between the data sets.

To calculate the coefficient of determination for financial instruments (GOOG, BAC, SPY, MCD, Spc1). Let's demonstrate the values of the coefficient of determination on the example of data from the archive (Cindicator analyst's forecasts and real values), calculated using an open library in Python:

```
from sklearn.metrics import r2_score
```

The obtained value of R^2:

GOOG: 0.8;

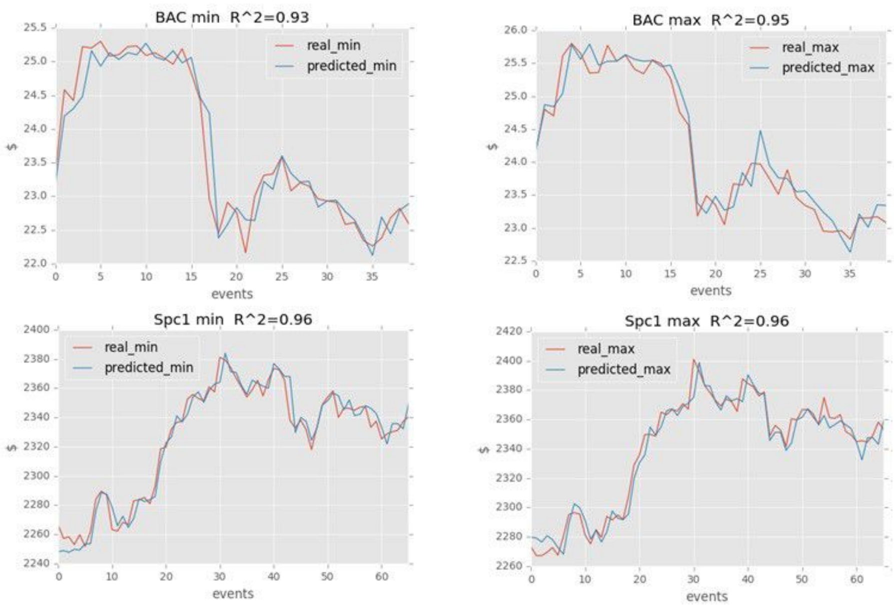
BAC: 0.93;

SPY: 0.94;

MCD: 0.9;

Spc1: 0.96.

For this calculations based on the data from data archive (forecasters predictions reality) used an open library on Python language: `from sklearn.metrics import r2_score`.



Conclusion:
Our experiments show the presence of a constant and strong correlation between analysts' forecasts and real market behavior. This means that we can implement a mathematical model that will extract from the forecasts of analysts the exact values of market behavior with the necessary accuracy.

5.4.2 Approach to the development of mathematical models

Predictions' accuracy of each forecaster varies depending on the type of question: some users provide great answers for questions related to macroeconomics and politics, while making mistakes in price-related questions; others, on the other hand, can accurately forecast price of a particular asset for next day/week/month, yet make mistakes in questions of other types. By researching behavior of each user we created self-learning system for assessment. For instance, depending on forecaster answers for price-related questions we can define 6 different forecaster profiles.

Wherein, behavior of the individual forecaster may vary: they predict only trends on weekdays (no time to look at the charts), but make more accurate forecasts on weekends. By applying different conversion operators, we can significantly improve prediction accuracy. In our models we take into account all behavioral patterns of the users.

We have found that there was a group of forecasters who are especially good at predicting the so-called bifurcation points, when the trend changes dramatically or experiences a sharp jump/fall. By constructing a separate algorithm for this cluster of forecasters, we can predict such bifurcation points and apply individual models to them.

Our models use different ML/DL approaches, such as:

- A Bayesian approach;
- Bayesian Belief Networks;
- HMM;
- Using various models as separate predictors which serve to build up the boosting;
- Building various regression models;
- Using various algorithms of clustering for segmentation and aggregation of forecasters. We compose clusters of superforecasters and ensembles of clusters, on which we run various algorithms;
- Using historical data on investment instruments in addition to user signals. Models based on time series analysis are also used.

5.5 Mathematical foundation

5.5.1 Definitions

We define:

Ω as a feature vector which characterizes a user;

$U_i(\Omega)$ as an i^{th} system user (forecaster);

$U = \{U_1 \ldots U_n\}$ as a user vector;

$E = \{E_1 \ldots E_m\}$ as a event vector;

$E^{real} = \{E_1^{real} \ldots E_m^{real}\}$ as real values (correct answers) vector for events E;

V_l — as an l^{th} ticker or E-belonging event voting operator.

Then, a *pure signal* for event l, not involving algorithms, is denoted by the following:

$$S_l = \frac{\sum_{i=1}^{w} V_l(U_i E_l)}{w} = \frac{V_l(\sum_{i=1}^{w} U_i E_l)}{w},$$

where w is the number of forecasts.

5.5.2 Superforecasting

The group $U_l = \{U_{l_1} \dots U_{l_m}\}$ is called *superforecasters* for events $E_k = \{E_{k_1} \dots E_{k_n}\}$, if

$$U_l =_U |V_k(UE_k^T) - E_k^{real}|.$$

The value $\epsilon_k^s = \max|V(U_l E_k^T) - E_k^{real}|$ is the *limit error for the group U_l at events E_k*.

5.5.3 Wisdom of the Crowd (WOC)

We define:

W as the user weights matrix;

W_l as the user weight vector for the event l;

$W_l^T U$ as the weighed users vector for the event l.

Then, the *WOC algorithm signal* is denoted by the following:

$$S_l = V_l(W_l^T U E_l^T).$$

The value

$$\epsilon_k^w = \max[V_l(W_l^T U E_l^T) - E_l^{real}|$$

is the *limit error of the WOC algorithm at events E_l*.

5.5.4 Model Boosting

We define:

$\mu^1 = \{\mu_1^1 \dots \mu_n^1\}$ as the *Superforcasting* models (forecasts) vector;

$\mu^2 = \{\mu_1^2 \dots \mu_n^2\}$ as the *WOC* models (forecasts) vector.

The following linear combination of models is called model *boosting*:

$$L = \sum \alpha_i \mu_i^1 + \sum \beta_i \mu_i^2.$$

In matrix form:

$$L = AM,$$

where $A = \alpha_i \beta_j$ is the coefficient (weight) matrix, $M = \mu_i^1 \mu_j^2$ is the model matrix μ^1 and μ^2.

We shall select a matrix $\dot{A}$, that

$$\dot{A} =_A |AM - E^{real}|.$$

The limit error of *model boosting* will be the following:

$$\epsilon^b = \max|\dot{A}M - E^{real}|.$$

Therefore, the following condition will be correct:

$$\epsilon^b <= min(\epsilon^s, \epsilon^w).$$

5.5.5 Sustainable Models

Let us consider the class of models $\hat{\mu}(\epsilon, \tau) = \{\hat{\mu}_1 \dots \hat{\mu}_n | \hat{\mu}_i \in \mu^1 \cup \mu^2\}$, for which the following *sustainability conditions* are laid:

1) $\forall t \in T_l^\tau$ $\dfrac{d(\mathbb{E}[E_t^{predict} - E_t^{real}])}{dt} = 0$, i.e. expectation of forecasts is a constant;

2) $\mathrm{Var}[E_t^{predict} - E_t^{real}] < \epsilon$, i.e. error distribution of expectation does not exceed ϵ;

3) $\mathrm{Var}[E_t^{predict} - E_t^{real}] < \mathbb{E}[E_t^{predict} - E_t^{real}]$, i.e. forecast distribution does not exceed expectation,

where $E^{predict}$ is the forecasted value (for any algorithm), $T_l^\tau = \{t_{k_1} \dots t_{k_\tau}\}$ is the time series of the ticker l.

Such a class is called *sustainable under the timing error.*

Theorem 1. *Let us assume that $\hat{\mu}(\epsilon, \tau)$ is the model class sustainable against the timing error, T_l^η is the time series for which $T_l^\eta > T_l^\tau$ Then:*

$\exists\ \chi : S \to S$ is the affine transformation at a set of signals, for which:

$$\lim_{t\to\infty} |\hat{S}_l - E_l^{real}| = 0, \text{ где } \hat{S}_l = \chi(S_l),\ t \in T_l^\eta.$$

Proof. *Let us prove that provided that Theorem conditions are met, there exists an affine transformation χ, for which $|\hat{S}_l - E_l^{real}| \searrow$.*

Without prejudice to communality, let us assume that all the forecasts are shifted upward, beyond the real value by $\gamma \leq \epsilon$ (inferred from the definition of a sustainable class). The case of downward shifting is proven analogically.

1) *Induction Basis. Let us assume that $\gamma < \epsilon$ is the forecast error for the moment $t_1 = T_l^\tau$, then let us set the shift $\chi(S_l) = S_l - \gamma$ as the transformation. We might note that the error for this case will be $\hat{\gamma} = 0$.*

   We shall add the forecast with the error $\alpha < \epsilon$ to the moment $t_2 = T_l^\eta$.

   Using the previous transformation, we then obtain that the error of the second forecast became as follows: $\hat{\alpha} = \alpha - \gamma$.

   We then see that without the transformation, the total error of two forecasts will be $\gamma + \alpha$, and $\alpha - \gamma$ with the transformation.

   It is obvious that $\alpha - \gamma \leq \gamma + \alpha$, as $\gamma \geq 0$.

2) *Induction Step. Let us assume that $\gamma_\tau = \{\gamma_1 \dots \gamma_\tau | \gamma_i < \epsilon\}$ denotes errors of forecasts in the time series $T_l^\tau = \{t_{l_1} \dots t_{l_\tau}\}$. Then the value $\gamma = \sum_i \gamma_i$ will be the total error in the series T_l^τ.*

   We shall take the transformation $\chi(S_l) = S_l - \mathbb{E}[E_t^{predict} - E_t^{real}]$, where $t \in T_l^\tau$.

   Let us then add the next forecast with the error $\alpha < \epsilon$ to the moment $t_{l_{(tau+1)}} = T_l^\eta$.

   Now we must prove that

$$\sum_i \gamma_i + \alpha \geq (\sum_i \gamma_i + \alpha) - 2\frac{\sum_i \gamma_i}{\tau},$$

   or

$$2\frac{\sum_i \gamma_i}{\tau} \geq 0.$$

As $\tau \neq 0$, while the sustainability conditions provide for $\sum_i \gamma_i \geq 0$, then the monotonicity statement will be correct.

Let us use the Weierstrass Theorem for the limited monotonic sequence:

> *Any monotonically increasing series, bounded from above (or monotonically decreasing series, bounded from below), has the limit equal to its least upper (lower) bound.*

Thus, we obtain that $\lim_{t\to\infty} |\hat{S}_l - E_l^{real}| = 0$. $\square$

All the models used in Cindicator hybrid intelligence technology, could be abstractly set out in the form of approaches given above. On account of the described theorem, there exists a model transformation for which error expectation reduces to zero in the time series.

5.6 Technologies (libraries, algorithms)

- **Languages:** Python, Scala, R;
- **Libraries:** NumPy, SciPy, Pandas, scikit-learn, matplotlib, seaborn, keras, Theano, xgboost;
- **Algorithms:** regressions, clusterisations, ARIMA, boosting, decision trees, random forest, deep learning;
- **Infrastructure:** Django/Flask/Tornado, Postgres, MongoDB, Re-dis, MS Azure, Hadoop, Spark.

5.7 Technological roadmap

In the future, as our technology develops and amount of data increases, we plan to:

- Implement neural networks and deep learning;
- Implement a trading robot based on reinforcement learning, which will independently analyse the market and learn from its own mistakes;
- Develop modern mathematical models to build predictive models for the market;
- Collaborate and cooperate with data scientists from leading universities (Stanford, Berkeley, Princeton, SPSU) and companies (Google Research, IBM) in finance, data science, and ML/DL;
- Create a platform for managing trading robots;
- Develop the market2vec algorithm (a vector representation of financial assets' data).

We believe that the merging of such areas as control dynamics, game theory and technical analysis, machine learning, and behavioural analysis is a very promising field.

6 Analytical products: completed and in development

Over 8,000 forecasters have made 230,000 forecasts since the global platform launch in December 2015. In July 2016 (once an adequate data set had been accumulated), the company started trading, forward testing and backtesting various trading strategies.

The main focus areas included two types of questions:

- binary probabilistic questions;
- price-related questions.

6.1 Binary probabilistic questions

Binary probabilistic questions are questions that only have two possible answers: yes or no. Forecasters have to give their answer as a 0%–100% probability for an event to happen. A 0%-49% probability is interpreted as a "no" answer with various degrees of confidence, while a 51%–100% probability is interpreted as "yes" with various degrees of confidence. As a rule, this type of question is used to forecast political, macroeconomic, corporate, and other sorts of events, as well as to forecast price movements to a certain degree.

Each analyst uses various strategies to answer these questions, as a specific probability value set out by a forecaster affects the number of points in the forecaster's rating*—that is, their financial motivation. Thus, each user is both an analyst and a risk manager for their portfolio on the platform.

For instance, some forecasters choose 40% or 60% for most questions; therefore, they can lose (if the answer is wrong) or gain (if the answer is right) 10 points maximum. Some forecasters only choose 0% or 100% to receive the greatest possible number of points (similar to traders, who use an equal risk per position in each trade). And some forecasters are cautious in events of great uncertainty and aggressive (0%–10% or 90%–100%) in events where they are more confident. Therefore, they are similar to traders, who risk bigger with greater confidence in a trade, and vice versa.

As a result, artificial intelligence models weigh the answers and assess forecasters over the history of their forecasts, as well as forming dynamically changing clusters (bulls, sheep, bears, superforecasters, etc). As a result, we get a valuable aggregate signal, which can be used in various trading systems and strategies.

Let's take a closer look at various types of binary probabilistic questions.

*The number of points is calculated as the difference between 50% and the user's answer. For instance, if a user chose 65% probability for the event "Will the Bitcoin price rise to $3,500 by July 30?" and the correct answer is "no," (i.e., 0%), they will receive 50 – 65 = -15 points. The forecaster who answers 10% for this question will get 50 – 10 = 40 points for their answer. Therefore, the maximum number of points available is 50. For more information, please see our FAQ.

6.1.1 Macroeconomic events

Macroeconomic events are the latest and most important economic events, figures, and facts that could affect financial markets. For example, we needed to find out the probability for the Federal Reserve's interest rate hike in June. To do so, we created the following question in the Cindicator app:

> *"The aggressively pro-US business approach of the Trump administration could prompt the Federal Reserve to hike rates more rapidly. Will the Fed raise the interest rate on Wednesday, 14 June?"*

In this case, the Hybrid Intelligence deemed the probability of a rate hike to be 66%, and in fact the Fed increased the rate at that meeting.

Regarding macroeconomic events, it is also possible to find out whether a macroeconomic indicator surpasses of analysts' expectations. For example, we are going to make a trade based on the publication of the ADP Employment Report, so we publish the following question in the Cindicator app:

> *"Last month ADP employment change was 172,000. The next report will be published on Wednesday, 3 August. Will employment rise by more than 165,000?"*

In this question, Cindicator forecasters predicted a 67% probability of ADP employment increasing by more than the consensus set. Indeed, that day, ADP employment change to 179,000. Thus, Hybrid Intelligence provided a correct forecast, and the market reacted in the right direction.

Let's adduce some more examples of similar questions related to macroeconomic events:

> *"Will the jobless rate in May be greater than or equal to 4.4%?"*
>
> *"Will China's second quarter GDP exceed estimates of 6.6% according to a report to be published on July, 14?"*
>
> *"Bank of Japan (BOJ) Governor Haruhiko Kuroda reiterated that the central bank is prepared to step up stimulus if needed, while noting again that so-called helicopter money is prohibited. Will BOJ cut interest rates to below -0.2% on the 28 July meeting?"*

Find out more about macroeconomic questions on our Medium blog, where we share the signals we receive and information on the trades completed based on this data:

- Nonfarm Payrolls: +3.7% in two minutes;
- Durable Goods Orders: How to Trade with Crowd Indicator?
- SPY: +0.3% on Fed's decision.

6.1.2 Corporate events

Speculation about whether a published report will exceed its consensus forecast is also used to predict some corporate events (e.g., quarterly reports). For this purpose, we put the following question to Hybrid Intelligence:

> *"Best Buy Co., Inc. (BBY) is set to report its second-quarter 2016 results on Tuesday, 23 August before the market opens. Wall Street is expecting earnings per share (EPS) of $0.43. Will Best Buy report EPS above Wall Street Consensus?"*

Cindicator predicted that Best Buy's report would be better than the analysts' consensus with a 73% probability. Indeed, the EPS published turned out to be higher than the consensus, and the company's shares spiked up by over 10% in one day.

Corporate events include not only report publication, but also dividend payment, conference calls, and presentations. You can see examples of trades, which can be made with the use of these forecasts, on our Medium blog:

Apple (AAPL) Conferences:

- Apple: +0.5% within a few hours;
- Apple: +5% in a few days.

Quarterly and annual reports:

- Guess? +13.2% in one trade;
- Apple: How to Trade with Crowd Indicator? +5.66% in one trade;
- Netflix: +17.7% in less than 24 hours.

6.1.3 Political events

Political events analysed on our platform include the election of top officials and parties in various countries, resignations, important meetings, certain political decisions (e.g., imposing or extending sanctions, or countries joining various coalitions), and others.

For example, prior to the first round of presidential elections in France, we posted the following question in our application:

> *"Less than two weeks before the vote in the first round, the far-right candidate Marine Le Pen was leading the polls in the 2017 French presidential election. The first round will be held on 23 April 2017. Will Marine Le Pen reach the second round?"*

Cindicator's Hybrid Intelligence generated an answer of 80%, and indeed, Marine Le Pen passed into the second round. After that, the following question was posted in the application:

> *"The first round of the 2017 French presidential election was held on 23 April 2017. As no candidate won a majority, a run-off election between the top two candidates, Emmanuel Macron and Marine Le Pen, will be held on 7 May 2017. Will Le Pen win the 2017 French presidential election?"*

On 6 May, 2017, Hybrid Intelligence deemed the probability of Marine Le Pen becoming president as 34%. On 7 May, Emmanuel Macron was elected President of France. Thus, Cindicator's Hybrid Intelligence accurately predicted the results of the presidential elections in France.

However, the answers received from Hybrid Intelligence, both correct and incorrect predictions, which need to be interpreted in the right way, can also be used as trading signals. For example, prior to the US presidential election, not many people believed in Donald Trump's victory, and Cindicator's forecasters estimated his chances of winning as 31%. However, US opinion polls showed that Trump and Clinton were keeping pace with each other. History shows that in such cases, when public opinion is so absolutely against facts (which show equal chances of both events), black swans often appear. In expectation of speculation around the election on 8 November, 2016, our analysts asked a number of questions and then completed several successful trades based on those questions. For more information, please see our blog on Medium:

- Volatility index: +3.14% in one trade;
- E-mini S&P 500 futures: +13% in less than 4 hours.

Thus, the signals received from Hybrid Intelligence can be inverted in some cases to complete profitable trades.

6.2 Binary price-related questions

In addition to questions related to events, binary questions are used when there is a need to determine price movement. For example, we need to know whether the price of an asset will rise to a certain level. By asking such a question, we receive an indicator that shows the probability of the price achieving this level.

For instance, on 7 October, 2016, we wanted an accurate price forecast regarding oil futures. Therefore, we posted the following question in the Cindicator app:

> *"Oil climbed above $50 a barrel for the first time since June as declines in U.S. crude inventories and OPEC's pledge to reduce supply lifted hopes the global glut may clear. Will WTI futures surge above $51.7 before 20 October?"*

We received the signal that the probability of such a price movement was 58%. On 10 October, the price rose to $51.6; our traders closed their position with profit of 1.9%, without further price increase expectations.

A question regarding the cryptocurrency FoldingCoin, put to Hybrid Intelligence on 15 June, 2017, is another example of a price binary event.

> *"The cryptocurrency FoldingCoin (FLDC/BTC) rose more than 16% and settled at 0.00000834 at 4 PM ET at Poloniex exchange on Thursday, June 15. Will FoldingCoin surge above 0.00001030 before 25 June?"*

Hybrid Intelligence answered "yes". Indeed, on 21 June, FoldingCoin exceeded 0.00001030. On 22 June, its price reached a peak of 0.00001642, showing almost 100% growth over the price at the time of the question being posted.

Binary signals can complement each other to create a comprehensive picture of the current market situation. Thus, the next example contains a binary question that was asked right after Netflix published its quarterly report and aimed at understanding the term of an increase in share price on the report:

> *"Shares of Netflix, Inc. (NFLX) closed the week ending 21 October 25.65% higher at $127.50 after the company reported far stronger-than-expected earnings per share on Monday, October 17. Will Netflix stock drop below $120 before November 5?"*

Hybrid Intelligence estimated such a probability at 34%. Indeed, until November 5, the price was above $120 per share.

Here's another example of making a trade using a series of questions. In May 2017, the market saw an adjustment of cryptocurrencies following a rapid increase. Cindicator posted a series of questions regarding Litecoin, which provided us with a signal to buy.

> *"The cryptocurrency Litecoin (LTC/USDT) settled on $30 at 7:15 AM ET at Poloniex exchange on Tuesday, 6 June. Will LTC/USDT drop below $22.50 before 25 June?"*
>
> *"The cryptocurrency Litecoin (LTC/USDT) settled at $28.32 at 4 PM ET on Poloniex exchange on Thursday, 15 June. Will LTC/USDT rise above $32 before 21 June?"*

According to Hybrid Intelligence, the answer to the first question was no, and the answer to the second question was yes. Thus, our traders purchased Litecoin with a stop below $22.50 using these signals. For more information, see our post on Medium: Litecoin: +80% in three weeks.

Here are some more examples of binary price-related questions:

- Oil Futures: Swing Trades with Crowd Indicator. +1.7% in a few days;
- Oil Futures: +2.3% in two days.

Binary signals show high accuracy: the average accuracy of this type of signal is 76% (the model is trained with over 300,000 forecasts).

Trading with the use of various binary signals as a main or auxiliary tool can provide interesting financial results. Thus, from July 2016 to February 2017, we increased our model portfolio by 123% by using only binary signals and trading on traditional markets.

Cindicator's model portfolio return (result of binary question interpretation), 18/07/2016 – 28/02/2017

You can see more examples of binary questions in this Google spreadsheet.

6.3 Price-related questions

Along with probability questions, Cindicator introduced price questions in January 2017. The questions were tested beforehand with a group of forecasters in a special challenge in October-December 2016, when the signals produced excellent results.

For example, we needed to get a trade signal and entry/exit prices based on minimum/maximum signals for Alphabet Inc. (GOOG) for Monday, 6 March, 2017. On Friday, 3 March, we created the following question in our mobile app:

> *"Shares of Alphabet, Inc. (GOOG) closed at $829.08 on Friday, 3 March. In your opinion, what will be the maximum and the minimum price of GOOG on Monday, 6 March during market hours?"*

Usually, in such events, forecasters can provide their prediction of the minimum and maximum price of financial assets before the market opens (in our example, before 9:20 AM ET, 6 March). Right after the question closes (deadline), the artificial intelligence system synthesises accurate forecasts using machine learning algorithms based on the accumulated statistics predicted by forecasters. Our system uses forward and back-tests of the history of synthesised predictions to calculate entry and exit points for GOOG shares with the optimal risk/reward ratio.

In this example, the signal was very accurate: the predicted minimum was $822.43, and the actual minimum was $822.40 (an error of 0.0036%); the predicted maximum was $828.81, and the actual maximum was $828.88 (an error of 0.0084%). The net profit for GOOG, after all transaction costs, amounted to 0.31% in two trades in one day. The charts below demonstrate the accuracy of the signals (all price levels are calculated by Hybrid Intelligence before market opening):

Another example: entry signals for SPY (SPDR S&P 500 ETF), 09/03/2017

Find more examples of min/max price signals on our blog:

- Amazon: +2.5% in a few days;
- Facebook: +0.66% in a few hours;
- Dollar Tree: +1% in just 2 minutes;
- Visa: +1% in just 20 minutes;
- Apple: +0.15% in one hour.

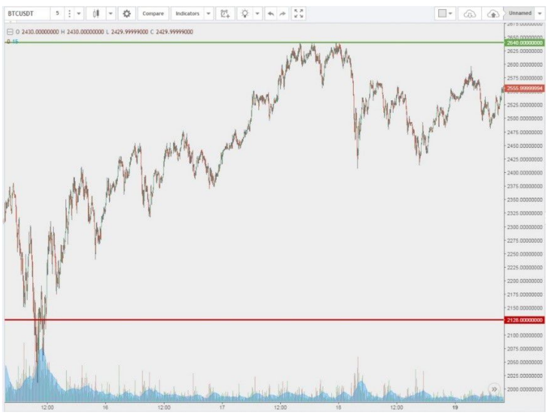
Similar to other Cindicator signals, min/max signals are universal and can be applied to any assets: cryptocurrencies, stocks, futures, currency pairs, etc. Also, generating these signals is possible for various time frames — e.g. daily, weekly, monthly, or quarterly. Specific questions related to the crypto-market, as well as questions with long-term time frames, is linked to higher volatility.

Our regular weekly crypto-signals are an example of how our technology deals with high volatility. Twice a week, we receive Hybrid Intelligence signals on the top three cryptoassets in terms of capitalisation: Bitcoin, Ethereum, and Ripple. For example, here is one of questions related to Bitcoin:

> *"[#WEEKLY]. The cryptocurrency Bitcoin settled at $2469 at 2:00 PM ET on Wednesday, 14 June. In your opinion, what will be the maximum and minimum price of BTC/USDT in over the next five days (from 10:00 AM ET on Thursday, 15 June until 9:59 AM ET on Monday, 19 June)?"*

The signals received with regard to Bitcoin question were quite accurate and are clearly represented on the following chart:

Bitcoin (BTC/USDT), 15/06/2017 - 19/06/2017



Similarly, the example regarding Ripple looks as follows:

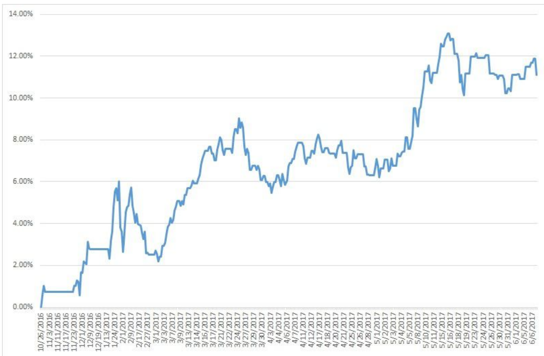
> *"[#WEEKLY]. The cryptocurrency Ripple settled at $0.2627 at 2:00 PM ET on Sunday, 11 June. In your opinion, what will be the maximum and the minimum price of XRP/USDT over the next 4 days (from 10:00 AM ET on Monday, 12 June until 9:59 AM ET on Thursday, 15 June)?"*

These signals also turned out to be accurate, which can be clearly seen from the chart below:

Ripple (XRP/USDT), 12/6/2017 - 15/06/2017

The min/max signals for price levels can be used to build numerous trading strategies or to serve as an indicator of important support and resistance levels. By using a simple counter-trend strategy (purchase at the min level and sell at the max level), we managed to reach a return of 11.68% on traditional markets from October 2016 to March 2017. From October 2016 to February 2017 trades were not carried out on a daily basis, so there were only 148 trading days. Thus, the annual profitability of this strategy was 19.8%.

The min/max signals return (selling at the max level, purchasing at the min level), 26/10/2016 - 06/06/2017



Examples of minimum-maximum price signals can be seen in this spreadsheet: link.

Such a strategy yields good results for crypto-assets, particularly Bitcoins. Weekly min/max signals described in detail above showed about 40% yield over the last six months (80% p.a.) with Bitcoin. At the same time, these signals are a countertrend, and the fact that they perform successfully in a trendy bull market is a matter of healthy optimism. Also noteworthy is the fact that this strategy works well on the short side too—short selling brought almost twice as much profit as longs (buying an asset), 22.31% vs. 13.96%, which is recognised as a solid gain in a bull market.

The min/max signals return for Bitcoins (selling at the max level, purchased at the min level), 13/01/2017 - 03/07/2017

6.4 Planned new data types, signals and indicators

Since 1 July 2017, a new type of price-related question has been added—questions pointing to a single price level. These may be questions related to the open and close prices of a financial asset, the price of an asset at a given moment, associated with reaching a certain level, and so on. For example:

> *"Shares in NIKE, Inc. (NKE) closed at $59 on Friday, 30 June. In your opinion, what will be the close price of NIKE stock on Monday, 3 July?"*

Since May 2017, we have also been testing a new type of signal on a group of forecasters who are consistently in the top 2% of the monthly rating. Users are required to choose assets that they think should be bought or sold (short selling), as well as assets for which transactions should not be made. Users should also provide stop loss and take profit prices for those assets that they choose to buy or sell. For example, the question is formulated as follows:

> *"What should we do with the cryptocurrency Ethereum (ETH/USD) in the coming week: buy, sell or nothing? The position will be opened at 9:30 AM ET on Monday, 22 May, and will be closed at 4:00 PM ET on Friday, 26 May."*

All forecasters provide their predictions for this asset. If they choose an action (buy or sell), they also need to set stop-loss and take-profit orders for their position. In this way each person can 'manage' their own investment position, choosing the expected direction and risk/profit parameters. For example, one of the users answers that Ethereum should be sold with a stop-loss of 199.9 and take-profit of 145.1; the second user chooses an option of buying (with a stop-loss of 120 and take-profit of 290); a third user indicates that nothing needs to be done, and so on.

Then it's the artificial intelligence algorithm's turn: it aggregates the forecasters' predictions into a single one, determining which action should be taken and with what parameters. In our example, Hybrid Intelligence decided that this week Ethereum should be bought with a take-profit of 196.62 and stop-loss of 129.78, on the condition that the position opens at the opening price at 9:30 AM ET on Monday. If neither the take-profit nor stop-loss is achieved, then the position will be closed on Friday. Indeed, Ethereum price increased, and this signal brought the model portfolio a profit of more than 32% over the course of five days.

For one month the profit on such signals was +12% in the stock market and +86% in the market of crypto-currencies (only three crypto-assets were used in trading: Bitcoin, Ethereum, and Ripple). We consider it an excellent result and plan to add such questions to the application in the near future.

The development of signals in which the task of Hybrid Intelligence is to rank assets on a certain basis is being actively pursued. For example, the companies conducting an ICO in the nearest month need to be arranged according to the degree of their probable success or trustworthiness. Each forecaster gets 100 points and the list of planned ICOs in the current month, as shown in the example below:

- AEternity
- Bancor
- Civic
- Cofound.it
- Monaco
- OmiseGO
- SONM
- Status

The forecaster should then rank the proposed ICO based on the degree of expected success (expressed, for example, in the growth of the price of a token over a certain period) or by personal trust therein. To do this, the forecaster distributes the 100 points among them, giving more points to companies expected to achieve greater success with the ICO.

The artificial intelligence system then aggregates the scores from all forecasters and determines which ICOs will be the most successful.

Tests for the stock market held in November 2016 (where forecasters were required to rank the shares of dozens of companies based on expected growth in their share price for the coming week) showed the consistency of these signals as a standalone indicator and as one of the support indicators in making investment decisions.

Another promising area of our research are signals in which forecasters need to specify a date in answering the question. For example, we are interested in this type of event:

> *"When do you think any G20 country will issue a national cryptocurrency?"*

Or this event:

> *"On what day will Ethereum break $1000?"*

A forecaster will name the date, and artificial intelligence, in its turn, will aggregate all predictions of forecasters into a single signal.

6.5 Planned new analytical products

The experiments we conducted and the results achieved by our colleagues studying various aspects of the operation of collective intelligence will enable us to create the following set of analytical products, which will be integrated into the overall capital management infrastructure:

- Assessing the power and influence of news on markets. Forecasters are offered N potential news hooks or events that will occur in the future and required to assess the direction of motion (whether this may lead to an increase or a drop in the price of an asset), as well as the impact of such motion;
- Uniting forecasters in centralised groups (depending on the predictions' accuracy in a particular cluster) and linking these groups to a decentralised structure (forecasters in a group collectively make predictions, which are further aggregated by artificial intelligence between different groups to create different data sets and trading signals);

- Access to analytics from superforecasters (signals exclusively from the top 2% ranked forecasters; channels for direct interaction with superforecasters for any category of interest, e.g., long-term Bitcoin analytics);

- Analysis of the existing investment portfolio of a particular trader by collective intelligence;

- A thermal geographic map of the market showing anticipated price increase/decrease for a certain asset. The map is compiled on the basis of predictions of forecasters from different regions. For example, US users taken together expect a 40% increase in Bitcoin over the next quarter, citizens of China expect 80%, and citizens of Germany only 5%. Thus, the map will explicitly show the distribution of expectations for the growth/decline of various assets.

6.6 Public experiment with Moscow Exchange

In January 2017, we launched a public experiment with Moscow Exchange (MOEX), one of Europe's biggest exchanges. Moscow Exchange is also one of the ten largest exchange platforms for derivatives trading globally (according to the World Federation of Exchanges monthly report statistics).

In this experiment, we completed trades based on the synergy of artificial intelligence and the collective intelligence of people with varied professional experience, united by a common goal. In addition, every participant had personal motivation.

To carry out this experiment, we collected a new sample of 925 unrelated people: 40% of the participants had never made trades on the exchange before; 60% had various investment experiences.

We received min/max levels (25,000 forecasts) from our forecasters regarding four financial assets (USD/RUB futures, Brent oil futures, silver futures, and gold futures) for three weeks on a daily basis, excluding weekends and holidays. After receiving forecasts, the robot aggregated them into a signal (including the entry level, stop loss, and take profit) and simulated the trades.

As the experiment was public, we posted all entry levels to our Telegram public channel on a daily basis prior to market opening.

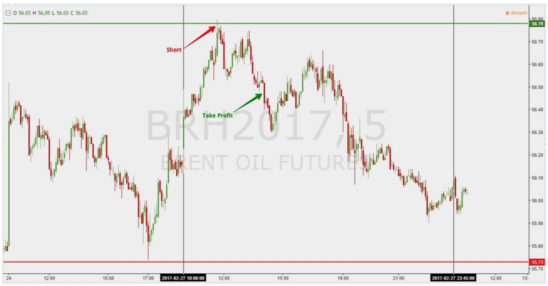
Based on the forecasts, Cindicator's robot modelled 57 trades, 36 of which were profitable, over the course of the experiment. The completed trades showed a 3.0% return in 29 days, which is equal to 26% p.a.

The result of this pilot proved the efficiency of the Hybrid Intelligence ecosystem even with a non-trained (on the computer learning models used by us) sample of forecasters.

Total gain, public experiment with Moscow Exchange from 19/01/2017 to 14/03/2017:

Entry/exit signals for USD/RUB exchange rate futures, 01/03/2017

Entry/exit signals for Brent oil futures, 27/02/2017



Entry/exit signals for Gold futures, 10/03/2017

Article highlighting the results of a public experiment with the Moscow Exchange (original post on the website of the Moscow Exchange).

Trades made during public experiment.

7 Team and stages of development

7.1 Team

The Cindicator team has been created by a synergy of like-minded people with a variety of expertise. About 85% of the team members are graduates of top STEM universities.

In 2014, Mike Brusov had the idea of creating an application for users where they can make various financial, political, and sports forecasts while competing with one another. Studying collective intelligence and the data generated by numerous diverse individuals was one of his professional activities in 2010. From 2010 to 2013, Mike, as one of the Wobot startup founders (an automated service for monitoring and analysing data generated by users in social media) studied the correlations between media coverage of numerous Internet posts that contained differing sentiments and realities.

In 2015, Mike collected the required initial investment and invited his future partners, Yury Lobyntsev and Artem Baranov, to join him in exploring the potential of collective intelligence.

Yury Lobyntsev has been working with computer systems and programming large-scale software systems since early childhood. At the same time he has been exploring the phenomena of intelligence, mind, and consciousness. In 2011, Yury founded his first tech business, the Oumobile studio, which is engaged in tech development for mobile startups.

In 2012, Artem Baranov established a digital product development company, which emerged from popular St. Petersburg local app Most Have. He is distinguished by his sense of style, laconic manner, and ability to apply new technologies in everyday life. Steady progress of the business required growth and strengthening of the companys position on the digital product development market - this was the reason for merging with Yury's team in 2014.

In 2014, Yury and Artem jointly established the Octabrain neurolaboratory, which undertook investment and R&D for startups and innovation projects. The company was working in the field of neurointerfaces (braincomputer interfaces), and neural networks. Through Octabrain, they organised a team of neuroscientists and digital product developers to explore and invent intelligent systems for human-machine interaction.

Mike, Yury, and Artem then united and began studying collective intelligence systems. After the release of the first version of the collective forecasting platform in December 2015, it was confirmed that among a random group of individuals there were 2% who very accurately predicted the answers to certain types of questions. Researchers Philip Tetlock and Den Gardner called these individuals superforecasters in their studies. It became clear that the wisdom of crowds' accuracy would be significantly enhanced by a statistical analysis of these forecasters accuracy.

Therefore, in 2016 the Cindicator team began growing its expertise in data science and machine learning. Data scientist Alexander Frolov was the first one who joined the team. After the arrival of the mathematician, teacher of mathematical methods, and backend developer, the technical team began to strengthen its mathematical and data analysis expertise in the domains of data processing and artificial intelligence modeling.

Following the decision to focus on finances and investments while building the ecosystem, Kate and Nodari joined the team: highly experienced in managing large positions, trading global stock, futures, foreign exchange, and cryptocurrency markets, these traders have worked in finance for over ten years. Their comprehensive expertise allows Cindicator to seek new ways to apply Hybrid Intelligence in various spheres of financial markets.

7.2 Current progress of the company

December 2015 saw the global release of the first iOS-based version of the platform. This was a step forward towards the creation of a collective intelligence system of the required size.

In January 2016, the team was invited to several startup accelerators and chose Starta Accelerator due to its location in the heart of the global financial system - New York. Once the acceleration program was successfully completed, Cindicator raised $300,000 during the pre-seed round of venture investment.

From June to November 2016, the team worked on the creation of the first set of machine learning models, the further improvement of the collective intelligence system (currently, there are over 8,000 forecasters on the platform), and the creation and forward testing of various trading strategies on the stock and foreign exchange markets. Intermediate results confirmed a number of hypotheses and provided interesting results.

In January 2017, an API for trading signals was launched, enabling the launch of test integrations with 11 hedge funds and three banks in the following four months. At that time, platforms were supplemented with the first crypto-assets, followed by internal experiments and related forward tests.

From November 2016 to March 2017, Cindicator took part in the first batch of the Moscow Exchange fintech incubator, where it was ranked as the top-performing startup. The company was granted $120,000 for technology development from Microsoft and became a member of the Microsoft BizSpark startup support program.

In April-May 2017, the company attracted $200,000 from a number of fintech investors in a seed venture round.

8 Legal considerations

8.1 Legal

We are have approached the Cindicator token sale in a comprehensive and responsible manner. Given the uncertain status of cryptocurrency and digital tokens in various jurisdictions, we spent a significant amount of time and resources to analyze the legal status of Cindicator business model and the CND tokens in jurisdictions where we plan to operate. In the United States, we worked closely with Velton Zegelman PC, a Silicon Valley law firm actively representing blockchain and cryptocurrency clients. In Gibraltar, the jurisdiction of Cindicator Ltd (Gibraltar) we are working with ISOLAS, a leading and oldest law firm in Gibraltar.

Due to the uncertain state of regulation on a global scale, we cannot guarantee the legality of Cindicator hybrid intelligence platform or ability to structure and license a future investment fund based on our platform in any given jurisdiction. However, we strive to be a responsive and compliant company should we face any regulatory inquiry.

8.2 Legal status of CND tokens

CND tokens are functional utility tokens designed for the Cindicator hybrid intelligence platform. CND tokens are not securities. Once you purchase CND tokens, they cannot be refunded. We do not recommend buying CND tokens for speculative investment purposes. You should buy CND tokens to participate in the Cindicator hybrid intelligence platform. CND tokens are not equated with participation in Vote, Inc. and/or Cindicator Ltd (Gibraltar) and CND token holders have no equity, governance, or any other rights in either company. CND tokens are sold as a digital asset, similar to downloadable software, digital music, and alike. We do not recommend purchasing CND tokens unless you have prior experience with cryptographic tokens and blockchain-based software.

8.3 Legal status of crowdsourced forecasting platforms

There is no unified regulatory framework applicable to crowdsourced forecasting platforms. These products and services are regulated in some jurisdictions based on existing gaming and/or financial services regulatory frameworks, while they are left unregulated in others. Before targeting a particular jurisdiction, we will conduct legal due diligence analysis of applicable regulations in such jurisdiction. Depending on the regulatory burden and steps involved, we will then either take the necessary steps to obtain any required licenses and/or permits in such jurisdiction or withhold from operating in such jurisdiction.

For the convenience of our users, Cindicator White Paper, website and other related documents are available in a number of languages. In the event there is any conflict between the English language version and a foreign language version, the English language version shall govern.

9 Conclusion

Cindicators ultimate goal is to set up a decentralised intellectual technology that effectively implements the potential of Hybrid Intelligence for the benefit of all participants of the ecosystem. In the future the technology strives to be fully automated: the only resource necessary for it to function will be the mental investment by the analysts.

Hybrid Intelligence anticipates being used not only in financial and economic markets, but also in art, politics, sports, business, technologies, and science in the future.

Cindicators token sale is an excellent opportunity to join the development of a symbiotic relationship between the minds of people and machines.

10 Risk factors and disclaimers

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