Flyingcarpet Network

Technical Paper

V2.1.1

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Introduction

The Flyingcarpet network connects analytics-hungry businesses with a pool of data scientists who compete to create machine learning/artificial intelligence analytics-extraction models from visual data, such as drone and satellite imagery. The competition incentivization mechanism uses bounties on a live physical location heat map and a Token-Curated Registry of Opportunities (TCRO) running on the Ethereum blockchain to collect and rank machine learning model creation opportunities. From insurance companies, to agri-companies, to governments, the Flyingcarpet network enables actionable insights through rich AI-powered analytics.

The Flyingcarpet utility token, Nitrogen (NTN), is used by data scientists to stake against the models that they create and used to stake against additions to the Token-Curated Registry of Opportunities (TCRO).

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The Market for Analytics

Flyingcarpet will sell analytics and predictions—extracted using machine learning models—to organisations and institutions. A coal trader may want to know when demand is going to exceed supply, thereby driving up prices. Using analytics extracted from satellite images, piles of coal outside power plants can be used to measure when power companies are low on coal and will need to refill. Drones can gather data about the number of coconuts or density of cacao per-square-meter in a plantation, before satellite imagery is used to count trains and track ocean tankers carrying the supplies. Flyingcarpet can provide predictions about who needs extra coal and who has a surplus to sell, in near real-time, giving traders leverage to negotiate sales and purchase agreements and create arbitrage opportunities.

Last year, Flyingcarpet built a machine learning model that enabled a drone to autonomously count the number of coconuts in a coconut plantation in Papua New Guinea—a task which cannot be performed using satellites. The aim was to increase estimation accuracy and reduce the costs of crop yield predictions for the farmer. From a 20-minute autonomous flight, we were able to effectively collect data from the entire plantation, provide an accurate coconut count, and translate it into crop yield predictions. In the future, this information could not only be used by the farmer to optimise distribution of fertilizers, water and so on, but could also be sold to commodity traders in different parts of the world to make better predictions of market movements. Flyingcarpet can also help other participants along the supply chains of sectors such as energy and commodities make better investment decisions. Farmers, shipment companies, wholesalers and retail stores can all benefit from increased price insights about particular commodities through Flyingcarpet machine learning models.

Aerial Analytics Industry Overview

The dramatically decreasing costs of space technology and transportation have led to the increased availability of high-resolution satellite imagery. This new data represents an analytics goldmine and, by 2027, big data analytics via satellites will generate close to $18.1bn.[4] This sector has already begun accelerating rapidly. In 2017 alone, AI-driven Earth-observation startups raised $96m—nearly three times more than in 2016.

Flyingcarpet combines visual satellite data with drone imagery to unlock new analytics and increasing resolution, speed and efficiency. According to a PwC study, the emerging global market for business services using drones will potentially exceed $127bn by 2020.[5]

Flyingcarpet's competitive advantage is its decentralization of the value resulting from the creation and use of machine learning analytics models. Data scientists directly capture the value of their efforts, businesses gain leverage over what analytics models are built and new investment opportunities are created for anyone to invest in the development of machine learning models. Flyingcarpet's unique incentive structure will form and harness a rapidly growing distributed community of skilled data scientists who help solve analytics challenges across many industries worldwide.

[4] http://www.nsr.com/research-reports/satellite-communications-1/big-data-analytics-via-satellite-2nd-edition/

[5] https://press.pwc.com/News-releases/global-market-for-commercial-applications-of-drone-technology-valued-at-over--127-bn/s/ac04349e-c40d-4767-9f92-a4d219860cd2

Infrastructure

From insurance (see the Insurance section below) to construction, Flyingcarpet has countless applications across infrastructure. One infrastructure initial use case we are particularly focused on is rooftop analysis. Using a machine learning model built on the Flyingcarpet network, a rooftop analysis consists of simply collecting data—by flying a drone over a building—and extracting analytics about the structure (e.g. roof abnormalities detection, structure size/volume estimation, etc.).

Drones, for example, offer the safest, quickest and cheapest option for assessing rooftops. Rich, effective insights collected by drones can help to locate and preempt potential hazards before they become costly expenses. In the United States alone, there are more than 300,000 commercial buildings that are each valued at more than $3m and more than 76 million single family homes, 83% of which are insured.[6] This massive potential market represents a mere subset of the entire commercial drone market, which is expected to reach $17bn by 2024.[7]

Agriculture

Aerial analytics—from both satellites and drones—may enable significant agricultural insights. The agriculture industry generates $2.4trn for the global economy each year.[8] From estimating crop yields to determining ideal use of resources for farmers, machine learning extraction models present an invaluable opportunity for the entire agriculture sector by unlocking rich insights. Flyingcarpet can cross-references the drone and satellite information with other relevant data, such as weather forecasts and the prices of agricultural products. This data can then be entered into machine learning software in order to track and calculate future food supplies with pinpoint accuracy.

Insurance

Analytics from satellite and drone imagery are also an ideal fit for the insurance claims industry. In 2016, net premiums written for the property casualty insurance sector totalled $533.7bn in the United States alone, according to S&P Global Market Intelligence. In 2017, only 38% of the economic cost from catastrophes was insured.[9] These insured costs can range from a strong, single earthquake in Japan ($125m) to seasonal flooding along China's Yangtze River Basin ($1.3bn).

Analytics extracted from regularly collected data can be used to rapidly and autonomously map locations before and after catastrophic events, allowing underwriters to manage their loss-earn ratios and to provide automated claims to customers. Such catastrophe risk modelling is key for property casualty insurance companies when setting insurance premiums, as the decentralised nature of the network would allow them to accelerate this modelling to improve underwriting decisions and determine when to cap portfolio exposure.[10]

A potential bypass of the insurance broker altogether will be possible by funnelling claims through the commission-less Flyingcarpet network. This would unlock enormous value by eradicating brokerage fees, which are often as high as 25%—and sometimes even 50%![11] Fundamentally, Flyingcarpet will help clients rebuild their communities in the quickest and most cost-effective manner possible, a process that currently can take years.

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[6] https://techcrunch.com/2017/09/05/betterview-just-raised-2-million-to-analyze-drone-footage-for-insurers/
[7] https://globenewswire.com/news-release/2018/02/28/1401040/0/en/Commercial-Drone-Market-to-hit-17bn-by-2024-Global-Market-Insights-Inc.html
[8] https://croplife.org/news/agriculture-a-2-4-trillion-industry-worth-protecting/
[9] http://thoughtleadership.aonbenfield.com/Documents/20180710-ab-analytics-if-june-global-recap.pdf
[10] http://www.ibmbigdatahub.com/blog/enhancing-catastrophe-risk-modeling-insurance
[11] https://cass-stephens.co.uk/insurance-broker-commission-disclosure

Other Use Cases

From analyzing oil inventory levels, to making predictions about the rate of polar ice cap melting, to mapping socioeconomic characteristics and patterns such as wealth and distribution of resources, the possibilities of analytics extraction from satellite imagery combined with drone and ground imagery are limitless. Companies, investors, traders, governments and nonprofit organizations can all benefit from these previously inaccessible analytical models.

Token-Curated Registry of Opportunities (TCRO)

Flyingcarpet uses a token-curated registry to collect opportunities for the creation of useful and valuable new machine learning models. Each new entry to the registry must include geographical location, information about the financially valuable analytics to be extracted and the expected revenue that will be generated by the future model. Registry entries are ordered by how many tokens are staked against each specific model creation opportunity. All Flyingcarpet network participants may submit locations for addition to the registry by staking Nitrogen (NTN).

The market for model creation opportunities exists as long as self-interested businesses continue to require analytics services. After entries are added, hardware owners, who use their devices to collect data, can reference the token-curated registry to position their hardware in profitable geographical regions. Additionally, data scientists may consult the token-curated registry to see what future machine learning model competitions will be run by the Flyingcarpet network.

Registry Curators

Anyone who holds Nitrogen (NTN) can act as a registry curator. However, we anticipate that data scientists will be the primary curators of the registry—as they will be significant holders of the Nitrogen (NTN) token and have a vested interest in which model competitions are run. The registry assigns curation rights proportional to the Nitrogen (NTN) token held by token holders.

Analytics recipients—such as businesses, commodity traders and governments—also have an incentive to hold the Nitrogen (NTN) token in order to influence which models are ranked highest on the registry; thus, leveraging the skills of the data scientists for their specific analytics needs.

Registry Candidates

Any Nitrogen (NTN) token holder can submit model creation opportunities for addition to the token-curated registry of opportunities. Businesses or governments, for example, may submit opportunities to the registry that align with their specific analytics needs—and subsequently fund these opportunities' bounties if they are added to the registry. Token holders must include a fixed amount of Nitrogen (NTN) as collateral against their submissions. If a submission is accepted into the registry, then this Nitrogen (NTN) is returned to the submitter. However, if the submission is rejected, the submitter loses their Nitrogen (NTN) and it is divided between registry curators. This collateral staking mechanism ensures submission of only legitimate model creation opportunities. Submissions to the registry must include the geographical location of the opportunity, information about the potential analytics that could be extracted and the expected future earnings from the model if it is built.

Registry Submission Reward

Because participants who submit model creation opportunities to the token-curated registry must assume financial risk by staking NTN, they are rewarded when entries they've added are used to create profitable analytics extraction models. These rewards are in the form of future royalty payments from revenue generated by the models that result from their registry submissions.

Collection Opportunity Discovery

Flyingcarpet provides a web-based heat map composed of data-rich opportunity locations from the token-curated registry for the purpose of helping "bounty hunters" to position their devices, like drones, to collect valuable visual data. Each collection opportunity may require specific device embedded hardware. Bountied visual data, required for models, may be gathered using any number of IoT devices, including drones, static cameras, charging stations and satellites—which may be more cost effective or provide more appropriate data for particular analytics-extraction use cases. Data collection bounties will initially be fulfilled manually; in the future, however, Flyingcarpet will provide a suite of open-source data collection software that enables autonomous drone flight, for example.

Device Owners

Flyingcarpet enables people, such as drone owners to provide their hardware on-demand for collecting data required for the creation and use of machine learning models. Device owners can use a web-based portal to discover data-collection bounties. A specific visual data bounty may, for example, require advanced hardware such as a thermal drone camera, so it is important that an existing market of these devices is available for data collection.

This system also opens up new income opportunities for device owners by enabling them to rent out their hardware. Completely autonomous on-demand data-collection drones may also be a valuable addition to the Flyingcarpet network in the future. Device owners who do not wish to operate their hardware themselves may allow third party data collectors to use their devices. Data collectors will also provide satellite imagery when it is required for models by simply accessing and uploading either public satellite imagery or visual data[12].

Bounty hunters

Flyingcarpet enable people to "hunt" data-collection bounties through the web-based portal which is composed of a google map with different point of data-collection bounties. Bounty hunters can use their own hardware or rent different on-demand hardware for collecting data required for the creation and use of machine learning models.

Human Dataset Classifiers

Proof-of-Existence (PoE) models that are created through the competition mechanism (see below for more information) are trained and tested using different datasets—collected by data collectors (outlined above). Human classifiers serve to manually annotate these training and testing datasets. Any participant can be a human classifier, including data scientists, device owners and model investors. Human dataset classifiers' incentives depend on the type of dataset they are collecting—training or testing.

Incentivisation of open-source training dataset classification is handled using Gitcoin bounties. A preset portion of funds raised for each TCRO model competition is dedicated to bountying the creation of an open-source training dataset. Creating high quality training data is in the interest of the entire Flyingcarpet community since training datasets are shared by all data

[12] planet.com

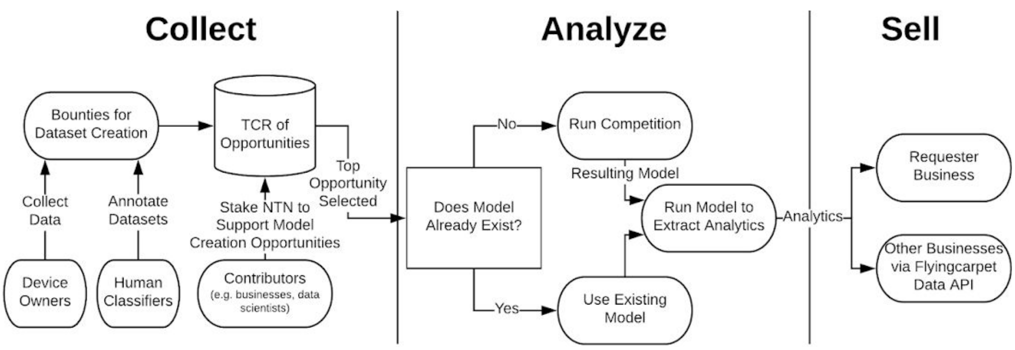
scientists creating models. Data scientists may also create (e.g. via a Gitcoin bounty) and use their own private training datasets to improve their models.

Because testing datasets are used to evaluate models in the competition, they must be encrypted and thus unavailable to competing data scientists until after a competition is complete. Instead of requiring human classifiers to annotate all data in the testing dataset—a daunting task indeed—each human classifier simply annotates a subset of the dataset, thus, each providing a sub-solution of the expected model output (e.g. the number of coconuts in a particular section of the collected footage or the number of abnormalities on a particular area of a rooftop). When submitting their subset output solutions, these human classifiers must stake a substantial fixed amount of Nitrogen (NTN) token as collateral against the quality and integrity of their manual classifications. After a competition is complete, the testing dataset is made public and a decentralized dispute mechanism is used to handle any objections raised by data scientists who participated in the competition. If no successful objections are raised about a testing dataset, human classifiers get their staked Nitrogen (NTN) back and receive a fixed cut from the competition staking pool (bounty) for their work. The percentage of this cut will be determined by a built-in democratic governance mechanism.

The job of human classifier on the Flyingcarpet network will present a remarkable income opportunity for people across the world, particularly in the developing world. For example, data entry workers in India currently earn approximately $1900 USD annually.[13] By working as a human classifier on the Flyingcarpet network, annotating imagery for model requests worldwide, a worker in India could earn significantly more for their work. Our vision is for the Flyingcarpet network to have a substantial global social impact by helping to create millions of higher paying jobs in the developing world over the coming decade.

Proof-of-Existence (PoE) Models

Businesses use bounties to commission data collection. Analytics are then extracted from the collected raw visual data using machine learning models. These models are sourced via a model creation competition where all successful data scientists benefit from the rewards. Finally, analytics are returned to the businesses and available to other businesses via a Flyingcarpet Data API.



Raw visual data is gathered and annotated during the Collect phase for both the training and testing datasets. Proof-of-Existence (PoE) models extract useful business analytics during the Analysis phase. These extracted analytics are then monetized in the Sell.

[13] https://www.payscale.com/research/IN/Job=Data_Entry_Operator/Salary

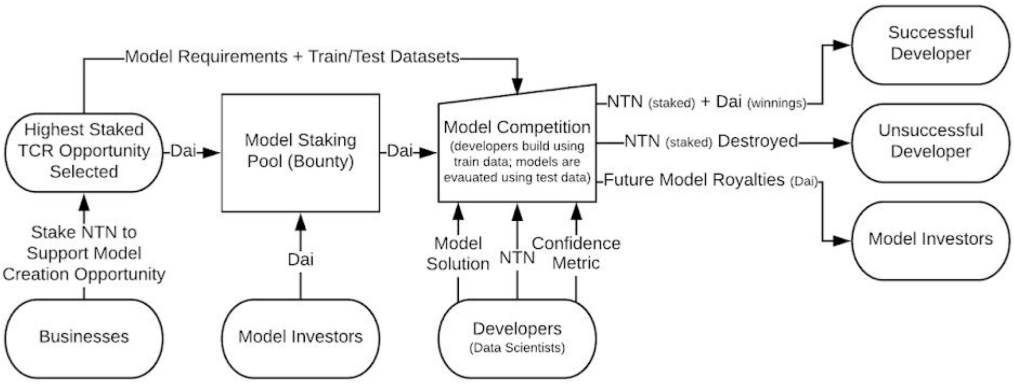
Collect

In order to run a machine learning competition for a new model, bounties are created—via the Bounties Network—for the collection of both the training and testing datasets required for the specific use case. Additionally, bounties are also used by businesses to request data collection for running existing machine learning models. These dataset bounties are viewable via our web-based heat map and can be fulfilled by any device owner whose device is equipped with the required embedded hardware to collect the desired type of visual data.

Analyze

After the raw data has been collected, a machine learning model must be used to extract the desired business analytics. If an adequate model already exists for the specific analytics, it is used for the extraction. However, if a model does not exist for the required analytics, then the desired model specifications are added to the Token-Curated Registry of Opportunities (TCRO). After participants stake against the model entry and it reaches the top of the TCRO, a competition is run where data scientists create, train and submit models.

The incentive mechanism for initiating a new model competition via the TCRO is designed such that if a participant locates an already existent model for the required analytics, they earn more money than they feasibly could through enabling the creation of the competition.



The machine learning model competition process flow.

A "staking pool" is setup to fund the TCRO model creation opportunity via a competition of data scientists. This pool is implemented through a bounty on the Bounties Network. In addition to businesses funding the pool, "model investors" are also allowed to participate. Model investors provide funds to the staking pool in exchange for a cut of the future revenue generated by the machine learning model. Anyone interested in a model investment opportunity may act as a model investor. All contributions to the staking pool are in the Dai stablecoin, however, through our business web portal, businesses will be able to easily pay with fiat currencies (the portal will have a real-time fiat-Dai exchange integration). The staking pool (bounty) is designed with a hard cap so that all competitions offer similar income opportunities for data scientists. This fixed competition hard cap will increase over time through a built-in governance mechanism as the number of data scientists grows and the amount of revenue generated through the Flyingcarpet network increases.

The purpose of the model investor participant is to abstract away investment speculation around future model revenue. This way, data scientists can focus on creating models and are paid immediately (when their models succeed in the competition). If data scientists do want to capture future model use revenue, they are allowed to participate as model investors also.

Both training and testing data for the model competition are provided by the data collected through bounties during the Collect phase (outlined above). Data scientists are provided with only the training dataset, the testing dataset (including sub-solutions) is encrypted and unavailable to competition participants.

After data scientists have built and trained their machine learning models using the competition training dataset, they submit their models to the competition. Each competition has a time limit after which the competition is closed and data scientists can no longer submit models.

When submitting their models, data scientists must also stake our Nitrogen (NTN) utility token and submit a metric of confidence indicating how well they believe their models will perform on the test dataset. Data scientists who submit successful models receive reward, R, in Dai stablecoin based on the amount of Nitrogen (NTN) staked, s, and the confidence metric, c (where $c \geq 1$ and a higher c indicates greater confidence in the model performance on the testing dataset), according to the following equation:

$$R = \frac{s}{c}$$

Thus, the network economically incentivizes honest judgement from the data scientists of their own models and disincentivizes overfitting of the model. After the models are submitted and the competition is closed, all models are run on the test dataset. A logloss function is used as a metric of model performance. Model analytics output is compared to the expected testing dataset output sub-solutions provided by human classifiers (see the Human Classifiers section for more information). Models that achieve a sufficiently low output from the logless function on the test dataset are considered successful, while models with a higher logloss are considered to have failed. Models are placed in descending order of their submitted confidence metrics, and, starting at the top, data scientists who submitted successful models are rewarded from the staking pool (a bounty) using the equation for R (listed above) and their staked Nitrogen (NTN) tokens are returned. On the other hand, data scientists whose models failed, have their staked Nitrogen (NTN) tokens destroyed. Once the staking pool has been exhausted, no more models are examined—the staked Nitrogen (NTN) for all remaining models is returned and no rewards are provided to those data scientists.

Finally, after the competition, the testing dataset is made open-source for public scrutiny. Any data scientist can raise objection to the testing dataset sub-solutions provided by the human classifiers—for example if a data scientist's model did not perform well. There is a fixed window of time when these dataset objections may be raised; after that, objections are no longer possible. In order to raise an objection, a data scientists must stake an amount of token equal to that of the human classifier. Conflict resolution is then handled via a decentralized court mechanism, implemented via an existing dispute resolution system. If a human classifier is found to be correct, then both parties' staked token is returned to the human classifier. However, if a human classifier is found to have made a mistake in their testing dataset sub-solution classification, both parties' staked token is returned to the data scientist who raised the objection, the winning model from the competition is voided and the competition is run again. If no legitimate objections are raised, a human classifier's token is returned to them and he or she earns a fixed cut of the staking pool.

Sale of Prediction Analysis

After a machine learning model has been run on raw data, the resulting analytics are monetized in two different ways through Flyingcarpet. Firstly, businesses who request analytics pay directly—whether requiring a new model or an existing one—in Dai (or Fiat through an exchange integration). Second, analytics that have been previously collected and extracted by models are continually available through the Flyingcarpet Data API. This API can be directly integrated into any application and enables access to rich data analytics. Flyingcarpet will not be a data marketplace; instead, Flyingcarpet will provide direct high-level analytics through our API for specific sectors of activity.

Open-Source Base Classifiers

In addition to building machine learning models from scratch, new models can be built on top of existing open-source base classifiers. Base models will be flexible and adaptable, that way they can be fine-tuned and trained for specific use cases. They will be open-source and developed by the Flyingcarpet community as a whole. Incentives to contribute to these open-source machine learning base classifiers will be provided to data scientists via existing solutions[14] by both Flyingcarpet and the community (e.g. businesses who have a particular interest in the development of a generalized base classifier for their use cases).

The Nitrogen (NTN) Token

The Flyingcarpet network has one native utility token called Nitrogen (NTN). The token serves a number of different purposes throughout Flyingcarpet, which are elaborated upon below. It is primarily used by data scientists to stake against the models they create for Flyingcarpet machine learning model competitions.

Generation

An initial large predetermined amount of Nitrogen (NTN) will be generated and disseminated to all registered data scientists. For a set amount of time—a few years—our smart-contract will release a fixed amount of new Nitrogen (NTN) tokens periodically and distributed them to currently registered data scientists, to help incentivize early adoption. Data scientists who register and receive Nitrogen (NTN) will only be able to use their new tokens to stake against models they create and submit in PoE model competitions, they will not be able to transfer new tokens—data scientists can only transfer tokens that they've previously staked against successful models (tokens that have been returned).

Proof-of-Existence (PoE) Model Competitions

As outlined in detail in the earlier Proof-of-Existence (PoE) Models section, The Nitrogen (NTN) token is used by data scientists to stake against models that they create. Their token is returned to them when their models are successful in competitions. On the other hand, tokens that they stake against models that fail in PoE competitions are irreversibly destroyed.

Staking for Addition to the Token-Curated Registry of Opportunities (TCRO)

The Nitrogen (NTN) token is also used by registry candidates who want to add opportunities to the Token-Curated Registry of Opportunities (TCRO), as explained earlier. Anyone who holds Nitrogen (NTN) can act as a registry curator with a degree of voting power relative to their Nitrogen (NTN) holdings—thus, data scientists will often also be registry curators. When a new

[14] Such as Gitcoin

model opportunity entry is accepted, the model candidate's staked Nitrogen (NTN) is returned. However, when a potential entry is rejected, the candidate's staked Nitrogen (NTN) is split between registry curators.

Complete Use Case Example

This section will examine and walkthrough an end-to-end use case example of the Flyingcarpet network. An energy provider, for example, requires a detailed analysis of a 20km stretch of power lines. In order to conduct a thorough risk analysis, drone footage will be used to discover any abnormalities in the lines and satellite data will be used to analyze potential weather and regional environmental risk factors.

First, using an intuitive UI "Google map" style on the Flyingcarpet webportal, the energy provider simply requests a model for their specific analytics needs. Their request then creates a model creation opportunity for data scientists via submission to the Flyingcarpet Token-Curated Registry of Opportunities (TCRO). If token holders feel that the entry is a viable model creation opportunity, it is added to the registry—since token holders are most interested in increasing the token value by improving the utility provided by network models. The top entry for the TCRO is selected to run the next model creation competition, thus, the energy provider will stake token against their new TCRO entry to help move it up the registry. When the top TCRO entry is selected to run a competition, the token staked against it becomes the staking pool. Thus, model investors interested in making money from the future royalties that will be generated by a model (once it's built) may also stake against the TCRO entry.

Bounties are made for creating both the training and testing datasets for the power lines TCRO entry. Each dataset consists of a collection of raw data combined with a definition of expected results (e.g. in the case of power lines, the number of line abnormalities, etc.). Both dataset collection and annotation requests are fulfilled via bounties. Thus, a drone owner, browsing bounties via the Flyingcarpet portal heatmap, sees the opportunity and earns the money by collecting and uploading the required raw data. The satellite data is also collected and provided via a bounty.[15] Human classifiers also fulfill bounties by manually annotating the raw collected data for training and testing the machine learning models submitted to the competition.

Once the energy provider's specific model task entry reaches the top of the TCRO, a machine learning model competition is initiated. All token staked against the TCRO entry is transferred into the staking pool—implemented via a bounty—to fund development of the model. Data scientists work to create effective and successful models that perform sufficiently well on the open-source training dataset, while attempting to avoid overfitting. When the competition time runs out, data scientists submit their refined models, express their confidence in the models they've created and stake Nitrogen (NTN) token. Models are assessed by running them against the testing dataset. Reward is distributed to data scientists with successful models based off of their provided confidence (see the Proof-of-Existence (PoE) Models for more information).

After the competition ends, the testing dataset that was used to evaluate the models is decrypted and made public. There is then a set window of time where data scientists can raise objections to the testing dataset if they feel that it's classifications were incorrect. To raise objection, data scientists must stake token and the dispute is handled via a conflict resolution system (see the Human Classifiers section for more information).

[15] planet.com

Finally, the energy provider runs the most successful model, via the Flyingcarpet network, to extract the analytics and insights they need to make informed decisions about the 20km stretch of power lines. Additionally, other interested parties can benefit from this power line analytics extraction model. For example, commodities traders could use these analytics to make informed bets for or against the energy provider (predictions of how expenses associated with power line damages will affect the company's quarterly earnings for example) or governments can use the analytics to assess national infrastructure conditions and develop plans of action in the event of power outages. Of course, these analytics will only be made available to secondary buyers with the consent of the initial paying business—the incentive being a secondary revenue stream for the business.

Initial Jump-Start Strategy

When the Flyingcarpet network is first started, demand for models will be low due to a lack of network effects. The Flyingcarpet team will use a portion of raised funds to jumpstart demand. The team will request commodity analytics models—such as estimates of agricultural crop yield or oil holdings—through the Token-Curated Registry of Opportunities (TCRO). The Flyingcarpet team will use these insights to make investments on communities futures markets, for example, and then reinvest all earnings back into the creation of more analytics models on the Flyingcarpet network.

This investment strategy is only a short-term catalyst to help jump-start network effects across the Flyingcarpet network. Once data scientists become aware of these earning opportunities, more will join the Flyingcarpet network and the demand for analytics models will increase.

Conclusion

Flyingcarpet is to visual data what Numerai[16] is to financial data. Flyingcarpet enables the creation and use of machine learning data-extraction models from physical data-collection bounties by harnessing the power of a community of data scientists that is incentivized through a unique token-economic mechanism. By competing individually for rewards in model competitions, data scientists fuel a collaborative ecosystem of value sharing; as data scientists add useful models to the network they increase the value for all token holders.

Flyingcarpet models operate on any form of visual data, including drone and satellite imagery. By maximising incentives for all participants, the Flyingcarpet network allows rich analytics to be extracted and sold globally. This will unlock tremendous value and efficiencies for countless sectors, including insurance, humanitarian aid, agriculture, supply-chain tracking, habitat preservation and infrastructure inspection, to name just a few. As a versatile network of visual data services—complete with efficient incentivization mechanisms—Flyingcarpet is positioned to radically disrupt the data analytics industry.

[16] Numerai