Flyingcarpet Network

Whitepaper

V2.3.0

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1 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, plane and satellite imagery. The competition incentivization mechanism uses bounties on a live geographical heat map and a Token-Curated Registry of Opportunities (TCRO) running on the Ethereum blockchain to collect and rank analytics-extraction opportunities. Flyingcarpet Oracles provide truth of the physical world—extracted by Flyingcarpet machine learning models—directly to smart-contracts. Businesses access these rich insights via the Flyingcarpet Analytics API. From traditional insurance companies, to decentralized parametric insurance DAOs, 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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2 Overview

Flyingcarpet is the decentralised geospatial analytics layer for the emerging Web 3.0 stack of permissionless Ethereum-based protocols. The Flyingcarpet protocol reports truths relating to the physical world by extracting analytics from geospatial data.

Flyingcarpet can either report these truths directly to organisations whose operations rely on geospatial analytics or—more interestingly—programmatically input them into smart contracts via Flyingcarpet oracles. Both scenarios will create immense economic opportunities for network participants; however, while the former provides analytics-hungry organisations with highly-specific insights, the latter is a novel solution to the "Oracles Problem" that, we believe, has deep implications for smart contract development.

Furthermore, unlike comparable geospatial services[4], Flyingcarpet distributes the value created on the network among all participants involved in the analytics extraction process. Data scientists directly capture the value of their efforts, hardware owners can monetise their devices in new ways, businesses can 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.

The Flyingcarpet Network is an end-to-end system of incentives that allows an end recipient—whether an analytics-hungry business or a smart contract dependent on some future event in the physical world—to request specific analytics without having to trust both the off-chain data source and the mechanisms that extract and report analytics from that data.

2.1 Geospatial Analytics

The Flyingcarpet Network connects organisations to data providers, whether they are satellite data providers, plane imagery providers or drone owners, and a global pool of data scientists who build analytics-extraction models that generate valuable geospatial analytics.

Last year, Flyingcarpet built a proof-of-concept machine learning model that enabled a drone to autonomously count the number of coconuts in a plantation in Papua New Guinea—a task that cannot be performed using satellites. After a mere 20-minute drone flight, we were able to collect data from the entire plantation, provide an accurate coconut count and translate this raw data into crop yield predictions, which resulted in immense cost savings for the farmer.

However, Flyingcarpet will not operate solely at such a granular level. A multinational energy firm that wants to cut the cost of manually inspecting each turbine in an offshore wind farm could use Flyingcarpet to radically cut costs and obtain better results. Like the Papua New Guinean farmer, the firm could request a specific data collection mission and then leverage Flyingcarpet's pool of data scientists to procure a highly specific analytics-extraction model that can be reused during future inspections.

Flyingcarpet also has an immense role to play in improving market efficiency. As outlined by Friedrich Hayek in his seminal "The Use of Knowledge in Society", the price mechanism is essentially the aggregation of all knowledge about a particular item at any given moment. And, yet, due to precise demand levels being different for each buyer in a market, the sum total of this information is too immense to ever be fully captured and so prices will always be somewhat imperfect.

[4] Orbital Insights who recently closed $50M series C funding from Sequoia Capital

Using Flyingcarpet, a coal trader in London can request that satellite images of coal piled up outside power plants are analysed in near real-time. She could combine these insights with near real-time analytics relating to coal trains and ocean tankers to obtain greater leverage when negotiating sale and purchase agreements. There is, of course, nothing stopping the buy-side from using the Flyingcarpet Network to request insights relating to the products they require, thereby eroding information asymmetries in the market, and contributing to more accurate pricing.

Entire supply chains and organisations of all types and sizes will benefit from the geospatial insights generated by the Flyingcarpet Network.

2.2 Proof-of-Existence Oracles

Smart contract use cases are restricted by the “Oracles Problem”: the difficulty of verifying the source of off-chain data and trusting the actor—the oracle—that communicates that data to the blockchain. Without trusted oracles, smart contracts are limited to automating agreements based on data that both already exists at the time of agreement and is currently stored on-chain.

Therefore, in order to radically open up how smart contract can interact with the physical world, Flyingcarpet models only generate analytics from trusted, verifiable data and are also capable of functioning as trust-minimised oracles. In respect of trusting data sources, this is achieved via the incentives described on page 8. Meanwhile, Flyingcarpet’s model creation competitions (see page 12) and use of human classifiers (see page 8) mean that successful models, which are stored decentrally with on-chain proof, can be continually used without any further trust requirement. The Flyingcarpet Oracles and Analytics API (see page 11) enables geospatial analytics generated by trust-minimised Flyingcarpet models/oracles to be integrated directly into smart contracts.

As such, Flyingcarpet facilitates a whole host of smart contract applications relating to the physical world, such as automated insurance plans that run through commission-less DAOs (see page 6), hedging instruments, and countless other use cases that have no parallel in the current economy.

3 Industry Use Cases

Developments in IoT hardware, such as satellites and drones, combined with advances in machine learning and artificial intelligence is rapidly unlocking new possibilities for geospatial analytics.

According to a PwC study, the growing global market for drone business services will exceed $127bn by 2020.[5] The dramatically decreasing costs of space technology and transportation have increased the availability of high-resolution satellite imagery. This data is a geospatial analytics goldmine; by 2027, big data analytics from satellite imagery alone will generate an estimated $18.1bn per annum.[6] This sector has already begun accelerating rapidly; in 2017 alone, AI-driven Earth-observation startups raised $96m—nearly three times more than in 2016.

[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

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

Flyingcarpet wraps these trends in a decentralised protocol with huge implications for both off-chain and, due to the network's oracles mechanism, on-chain activity that involves—or, indeed, relies on—geospatial analytics.

3.1 Infrastructure

From insurance (see Section 3.3) to construction, Flyingcarpet has countless applications across infrastructure. One initial infrastructure use case we are 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.[7] This massive potential market represents a mere subset of the entire commercial drone market, which is expected to reach $17bn by 2024.[8]

3.2 Agriculture

Geospatial analytics—from both satellites and drones—offer significant agricultural insights. The agriculture industry generates $2.4trn for the global economy each year.[9] 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-reference 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.

3.3 Insurance

Analytics from satellite, plane 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.[10] 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. By attaching a predetermined payout to a specific event (instead of a specific loss amount) claims can be automated, cutting cost and time inefficiencies out of the process. This is called 'parametric' insurance and is a perfect match for blockchain and smart contracts. Flyingcarpet can take parametric insurance further, by using effective analytics-extraction models as oracles to not only prove that an event has occurred, but to provide proof that it caused a specific amount of damage by comparing post and pre asset states.

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

Such catastrophe risk modelling is key for property casualty insurance companies when setting insurance premiums, as the decentralised network would allow them to expedite this modelling, improve underwriting decision accuracy and better determine when to cap portfolio exposure.[11]

3.4 Decentralized Insurance (DAO Oracles Use Case)

A potential bypass of the insurance broker altogether is possible by funnelling claims through commission-less decentralized insurance DAOs.[12] This new incentive structure unlocks enormous value by eradicating brokerage fees, which are often as high as 25%—and sometimes even 50%[13] Fundamentally, completely disintermediated insurance help clients rebuild their communities in the quickest and most cost-effective manner possible, a process that currently can take years.

Flyingcarpet oracles make these DAO insurance applications possible, opening the door to an array of disruptive new decentralized parametric insurance possibilities. By analyzing both pre- and post-catastrophe aerial imagery, state changes are used to assess the extent of damage and trigger instant payouts. For example, when a crop field is insured via a decentralized insurance DAO, satellite imagery is collected regularly and analytics are extracted to determine the current state of the field. After a storm occurs, the new state is compared to the state prior to the storm, and, if the extent of the damage exceeds a set threshold, an instant, automated payout is triggered.

Additionally, Flyingcarpet oracles enable “Nano” parametric insurance, whereby small distinct geographical items (e.g. part of a structure) or plots (e.g. 1 metre of of an agricultural crop field) are individually insured by a parametric insurance DAO. In this way, while parametric claim payout amounts are fixed, by reducing the size to “Nano” parametric insurance policies, damage assessment is handled separately for each independent portion of a structure or crop field for example.

3.5 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.

4 Core Network Participants

The Flyingcarpet Network incentivises multiple categories of participant in order to leverage the wisdom of the crowd and extract valuable analytics from raw geospatial data.

4.1 Organisations

Organisations across the world, whether they are businesses, governments or even DAOs, either use geospatial analytics to inform their operations or would greatly benefit from doing so. Financial value enters the Flyingcarpet Network when organisations post model creation opportunities on the Flyingcarpet Token-Curated Registry of Opportunities, which is described

[11] http://www.ibmbigdatahub.com/blog/enhancing-catastrophe-risk-modeling-insurance
[12] https://etherisc.com/
[13] https://cass-stephens.co.uk/insurance-broker-commission-disclosure

in Section 5, or when they purchase analytics either via Flyingcarpet Oracles or the Analytics API, as outlined later in the paper.

4.2 Geospatial Data Providers

Data providers are companies or individuals who use their devices to provide specific geospatial data required for analytics extraction opportunities. In Section 2, we referred to large satellite imagery providers as well as individual drone operators but the Flyingcarpet Network will accommodate an entire spectrum of data providers, including planes and static cameras. In order to incentivise data providers to collect data, they receive a share of the bounty pool for each analytics-extraction opportunity.

4.3 Data Scientists

Primarily data scientists compete in Flyingcarpet model creation competitions (see Section 6) by building analytics-extraction models. However, as outlined in Section 5, they also play a critical role in annotating the training and testing datasets that are critical to verifying the integrity of the models, which thereby ensures that models can function as trust-minimised oracles.

5 Token-Curated Registry of Opportunities (TCRO)

Flyingcarpet uses a token-curated registry to collect opportunities for analytics extraction. 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. If no existing machine learning model exists for the required analytics, data scientist competitions are used to incentivise model creation.

The token staked against a TCRO entry are used to fund the required data collection as well as the model competition—if no adequate model already exists. Registry entries are ordered by how much token is staked against each specific opportunity. All Flyingcarpet network participants may submit opportunities for addition to the registry by staking Nitrogen (NTN).

The market for data-extraction opportunities exists as long as self-interested businesses continue to require analytics services. After entries are added, hardware owners ("bounty hunters") make money by collecting and providing raw data for the required analytics. Each data scientist competition is run based on the current highest staked TCRO entry (that does not have an existing model to extract the needed analytics). Data scientists may also consult the token-curated registry to see what future machine learning model competitions will be run.

5.1 Registry Curators (Model Investors)

Anyone who holds Nitrogen (NTN) can act as a registry curator (also known as a model investor). However, we anticipate that businesses will be the primary curators of the registry, as they will have a vested interest in which opportunities are fulfilled—they desire analytics for their specific needs. The registry assigns curation rights proportional to the amount of Nitrogen (NTN) token held by token holders.

Analytics recipients—such as businesses, commodity traders and governments—have an incentive to hold the Nitrogen (NTN) token in order to influence which opportunities are ranked highest on the registry and thereby leverage bounty hunters and data scientists for their specific analytics needs.

Model investors receive a cut of the future revenue generated by a machine learning model. 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 both help curate a list of highly viable analytics extraction opportunities, and abstract away investment speculation around future model/analytics revenue. This way, data scientists can focus on creating models, bounty hunters can spend their time hunting data collection opportunities and both are paid immediately (for successful work). If data scientists or bounty hunters do want to capture future model use revenue, they are, of course, able to participate as model investors also.

5.2 Registry Candidates

Any Nitrogen (NTN) token holder can submit opportunities for addition to the token-curated registry. Businesses or governments, for example, may submit opportunities to the registry that align with their specific analytics needs by staking the opportunities' bounties. Submissions to the registry must include the geographical location of the opportunity, information about the potential analytics to be extracted and the expected future earnings.

5.3 Registry Staking Reward

Because participants who stake against TCRO opportunities must assume financial risk, they are rewarded when entries they've funded are used to generate profitable analytics. These rewards are in the form of future royalty payments from revenue generated by the models and analytics that result from registry opportunities they have funded.

5.4 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" position their devices, like drones, to collect valuable visual data. Collection opportunities may require devices with specific 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; Flyingcarpet will, however, work to develop and provide a suite of open-source data collection software that enables, for example, autonomous drone flight.

5.5 Device Owners (Bounty Hunters)

As described in Section 4.2, Flyingcarpet enables individuals to provide their hardware on-demand for collecting data required for the use and creation of machine learning models via TCRO entries. Device owners, also called "bounty hunters", 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. 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 private aerial data sources[14].

5.6 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 a bounties system[15] . A preset portion of funds raised for each TCRO entry 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 scientists creating models. Data scientists may also create (e.g. via a Bounties Network 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 TCRO entry staking pool (bounty) for their work. The percentage of this cut will be determined by a built-in democratic governance mechanism.

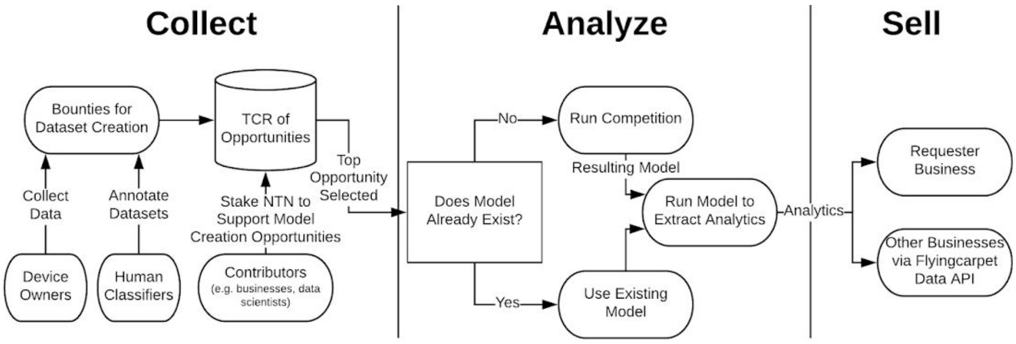
The job of human classifier on the Flyingcarpet network will present a remarkable income opportunity for people across the world, particularly in the developing world. For example, data entry workers in India currently earn approximately $1900 USD annually.[16] By working as a human classifier on the 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.

6 Proof-of-Existence (PoE) Models

Bounties are used to commission data collection for both creating and using models. Analytics are extracted from collected raw visual data using machine learning models. These models are

[14] planet.com
[15] https://gitcoin.com
[16] https://www.payscale.com/research/IN/Job=Data_Entry_Operator/Salary

sourced via a model creation competition where all successful data scientists benefit from the rewards. Analytics are made available to businesses via the Flyingcarpet Oracles and the Analytics 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.

6.1 Collect

Raw geospatial imagery is provided to the Flyingcarpet network from three different sources: satellites, planes and drones. Satellite and plane data is provided by highly reputable, global data companies. For satellite imagery we are working with Planet.com and Urthecast; while for plane imagery we're working with Nearmap (for US and Australian data).

For drone data, bounties are created for raw data collection. These data collection opportunity bounties are viewable via our web-based heatmap and can be fulfilled by any device owner (also called a "bounty hunter") whose device is equipped with the required embedded hardware to collect the desired type of geospatial drone data.

In order to ensure the legitimacy of raw data collected by drones, bounty hunters must stake token along with their raw data bounty fulfillments. Once the bounty hunter data is submitted, opportunity investors—who have a vested interest in the integrity of the provided raw data—may review the provided raw data. If the collected data is malformed, illegitimate or otherwise incorrect, opportunity investors may challenge the data collection fulfillment bounty. The challenge is resolved by either the challenger or the data provider losing their stake to the other party using a griefing mechanism as presented in Erasure protocol[17].

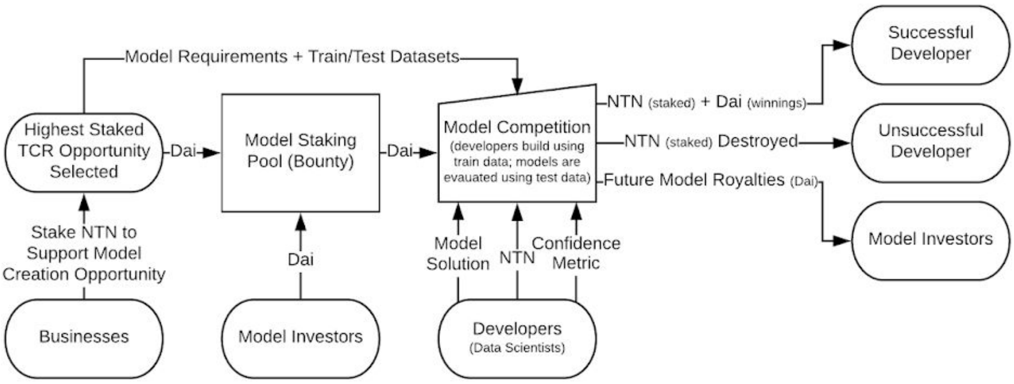
In addition to sourcing raw data for analytics-extraction using existing models, if a new model competition is needed, both the training and testing datasets required for the specific use case are also collected via this heatmap of data collection bounties.

6.2 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, once the TCRO entry reaches the top of the registry, a competition is run where data scientists create, train and submit models.

[17] https://medium.com/numerai/numerai-reveals-erasure-unstoppable-peer-to-peer-data-feeds-4fbb8d92820a

The incentive mechanism for initiating a new model competition 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.

All token staked in support of a TCRO entry by model investors is converted into a "staking pool" to fund a competition of data scientists to create the required model. This pool is implemented through a bounty.

Both training and testing data for the model competition are provided by the data collected through bounties during the Collect phase (see Section 6.1). 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 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 Section 5.6). Models that achieve a sufficiently low output from the logloss 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 scientist 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.

6.3 Sale of Analytics

Once the required raw data has been collected and a model sourced—either an existing model or a model one created via the competition mechanism—rich analytics can be extracted for businesses. Businesses pay directly in Dai (or fiat through an exchange integration).

Access to both previously extracted analytics and existing models (for additional data extraction) are continually available through Flyingcarpet Oracles and the Analytics API. These Oracles and API can be directly integrated into any smart-contract or application and enable access to rich data analytics. Flyingcarpet will not be a data marketplace; instead, Flyingcarpet will provide direct high-level analytics for specific sectors of activity. Additionally, Flyingcarpet will integrate with existing data marketplaces, such as Numerai's Erasure[18] marketplace, enabling the creation of Flyingcarpet models for specific, targeted Erasure predictions.

Model investors receive royalties in the form of Dai whenever models they've invested in, or analytics extracted by models they've invested in, are purchased by businesses. Due to this dual revenue stream, model investors are incentivised to fund opportunities that they believe will produce both one time rich analytics (specific to the geographic area of the opportunity), and reusable generic models—in the case of opportunities that require the creation of new models.

6.4 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[19] by both Flyingcarpet and the community (e.g. businesses who have particular interests in the development of generalized base classifiers for their use cases).

[18] https://medium.com/numerai/numerai-reveals-erasure-unstoppable-peer-to-peer-data-feeds-4fbb8d92820a
[19] Such as Gitcoin

7 Flyingcarpet Oracles and Analytics API

Flyingcarpet Oracles serve to provide smart contracts with a consistent source of truth about the physical world, while the Flyingcarpet Analytics API provides traditional businesses with easy access to diverse, rich analytics. Flyingcarpet oracles may be integrated directly into smart-contracts, for continual real-time access. Both previously extracted analytics (model output) and existing models may be accessed using Flyingcarpet Oracles and the Analytics API.

7.1 Previously Extracted Analytics

Analytics resulting from model execution requests are provided directly to businesses; additionally, these extracted analytics are saved, via decentralized storage (e.g. Swarm, IPFS, etc.), and made continually available via our oracles and API. By providing the specific geographical location and insight type of the desired analytics, businesses can readily access all available past model output.

Of course, when businesses request analytics they have the option to prevent onselling by restricting the use of the extracted insights to themselves. However, businesses that enable onselling via the oracles and API will be rewarded by future royalties when analytics they requested are used.

7.2 Existing PoE Models

Businesses can request new analytics via the TCRO. When a request is made, data is collected and processed by an existing PoE model (see Section 6 for more information on this process). The resulting analytics are then returned to the business. If no appropriate existing model is available for the desired analytics, the PoE model competition mechanism is used to create a model for the specific use case.

8 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.

8.1 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).

8.2 Proof-of-Existence (PoE) Model Competitions

As outlined in detail in Section 6, 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.

8.3 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 (model investor) with a degree of voting power relative to their Nitrogen (NTN) holdings—thus, businesses will often also be registry curators. Each registry curator receives future royalties from the models and analytics that result from TCRO entries that he or she funds.

9 Complete Use Case Example

This section walks through an end-to-end use case example of the Flyingcarpet network. An energy provider, for example, requires a detailed analysis of a 20 km 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 "Google Maps" style UI on the Flyingcarpet webportal, the energy provider simply requests analytics based on their specific needs. Since no machine learning model currently exists for the analytics that are required, their request spawns a model creation opportunity for data scientists via submission to the Flyingcarpet Token-Curated Registry of Opportunities (TCRO). Model investors interested in making money from the future royalties that will be generated by the model (once it's built) and resulting analytics stake against the TCRO entry. The top entry from the TCRO (most staked) that requires the creation of a new model 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.

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.[20] 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 entry reaches the top of the TCRO, a machine learning model competition is initiated. All token staked in support of 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 (whose models were successful) based off of their provided confidence (see Section 6 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

[20] planet.com

scientists must stake token and the dispute is handled via a conflict resolution system (see Section 5.6 for further information).

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.

10 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—by submitting opportunities to the Token-Curated Registry of Opportunities (TCRO).

The Flyingcarpet team will use these insights to provide predictions on Numerai's Erasure prediction marketplace. Using Flyingcarpet analytics as a source of truth, the team will make accurate predictions on the Erasure marketplace, and earnings from the sale of predictions will increase over time as a track-record of accuracy builds up. The team will 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.

11 Conclusion

Flyingcarpet is to visual data what Numerai is to financial data.[21] By incentivising data scientists through a unique token-economic mechanism to participate individually in model creation competitions, the Flyingcarpet Network fuels a collaborative ecosystem of value sharing. In other words, as data scientists build useful models on the network, they draw more organisations to the network and thereby increase the value for all token holders.

Flyingcarpet models operate on any form of geospatial data, including drone, plane and satellite imagery. By maximising and aligning incentives for all participants, the Flyingcarpet network enables AI-powered, geospatial analytics to be extracted and sold to businesses via the Flyingcarpet Analytics API.

Furthermore, Flyingcarpet Oracles enable models to report geospatial data back to the blockchain, which opens up countless new DAO use cases, such as automated parametric insurance claims, verification of land protection for charitable DAOs, and on-chain hedging contracts.

From agriculture, insurance and humanitarian aid to supply-chain tracking, habitat preservation, and infrastructure inspection, Flyingcarpet unlocks tremendous value and efficiencies. As a versatile network of geospatial analytics services—complete with efficient and well-aligned incentivization mechanisms—Flyingcarpet is positioned to radically disrupt the data analytics industry.

[21] https://numer.ai/