Flyingcarpet Network

The Earth observation layer for Web3

Whitepaper
V2.4.1

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1 Introduction

Flyingcarpet is an open analytics layer that incentivises data scientists to build a decentralised library of machine learning models that generate insights about the physical world from raw geospatial data.

Paying entities, such as businesses, governments or even decentralised autonomous organisations (DAOs) submit requests for geospatial analytics-extraction. Data scientists compete in model creation competitions—not dissimilar to those run by Numerai—using data submitted by trusted providers.[4] Successful models are stored decentrally for future use by paying organisations and a corresponding model ownership ERC-721 non-fungible token (NFT) is minted. Traditional businesses can purchase analytics from models, while (DAO) smart contracts can access model analytics via oracles.

Model ownership NFTs—that receive all revenue each time the corresponding model is used—are held by ERC-20 Bonded Curve Tokens[5]; as such, these intrinsic ownership NFTs encapsulate all future model revenue. The creation of each new model will present a unique opportunity for investment. In the future, these NFTs may function as tradable assets, where DAO funds build up diversified model ownership NFT portfolios, which individuals can, in turn, invest in.

The Flyingcarpet Network will improve access to high-quality geospatial insights, while creating new economic opportunities for data scientists. Furthermore, Flyingcarpet model oracles will have immense implications for smart contract development and DAOs, providing a trustworthy link to the physical world. Lastly, Flyingcarpet models will enable anyone in the world—with even a small amount of capital—to effectively invest in and capture the value of the world's geospatial data.

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2 Overview

Flyingcarpet is the decentralised geospatial state determination layer for the emerging stack of permissionless protocols based on blockchains, such as Ethereum. The Flyingcarpet protocol reports truths relating to the physical world by incentivising data scientists to build a decentralised library of machine learning models that extract analytics from raw 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 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, will contribute enormously to the development of the global decentralised ecosystem.

Unlike comparable geospatial services, Flyingcarpet distributes the value created on the network among all participants involved in the analytics-extraction process.[6] Data scientists directly capture the value of their efforts; data providers monetise their data in new ways; businesses can influence which 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 organization or a smart contract dependent on information about future events 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 the analytics from that data.

2.1 Geospatial Analytics

The Flyingcarpet Network empowers organisations with rich geospatial analytics through a unique incentive structure that harnesses a global pool of data scientists to build insights-extraction models from satellite imagery. Although satellite imagery is the network's primary data source, the Flyingcarpet team intends to extend the protocol to eventually extracting insights from plane and drone imagery.

A multinational insurance firm that wants to cut the cost of manually inspecting each building following a natural disaster, which ranges from $140-$300 per roof, could use Flyingcarpet to radically cut costs, expedite claim payout times and obtain better results.[7] The firm would leverage Flyingcarpet's pool of data scientists to access a highly specific analytics-extraction model that can be reused for 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", pricing mechanisms essentially aggregate 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. Flyingcarpet enables geospatial "knowledge"

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

[7] https://www.angieslist.com/articles/how-much-does-roof-inspection-cost.html, https://dronesaferegister.org.uk/blog/2018/08/27/what-does-a-roof-inspection-cost-uk

to inform the market in near real-time and will therefore improve decision-making around pricing on the both the buy- and sell-side.

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.[8] 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.

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.

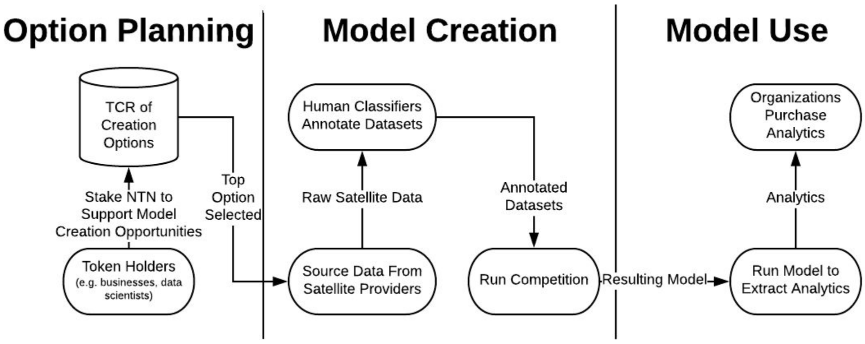
In order to radically open up how smart contracts can interact with the physical world, Flyingcarpet models only generate analytics from verifiable data provided by satellite partners with ironclad reputations. The Flyingcarpet Analytics API (see Section 9) enables Flyingcarpet models to functions as oracles and therefore enables insights into the physical world 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 claims that run through commission-less DAOs (see Section 3.4), hedging instruments, such as commodities futures that are dependent on geospatial factors rather than price indices, and countless other use cases that have no parallel in the current economy.

3 The Flyingcarpet Network as a Decentralized Application

This section briefly touches on the Flyingcarpet Network's architecture, different network participants, the model investment process and user interface.

3.1 Architecture Overview



The Flyingcarpet Network aligns incentives between all participants through the Nitrogen (NTN) and NitrogenX (Nx) utility tokens, which are detailed in Section 4. Organisations that require analytics can

[8] Descartes Analytics

submit a model creation request, along with details of the analytics they require and a geographical location so that Flyingcarpet's satellite partners can provide a relevant geospatial dataset, on the Geospatial Dashboard (see Section 5). Human classifiers annotate training and testing data for each model creation request via the Annotation Portal (see Section 6). A distributed community of data scientists then compete in model creation competitions (see Section 7) in order to aggregate the "wisdom of the crowd" and produce the optimal analytics-extraction model for the organisations particular needs. Successful models are displayed on the Models Dashboard, from which organisations can continually purchase analytics that are priced according to predefined NTN/Nx bonding curves (see Section 8). Once purchased, analytics are made available via the Flyingcarpet Analytics API (see Section 9). Disputes that arise on the network are resolved via a decentralised arbitration mechanism (see Section 10).

3.2 Network Participants

The Flyingcarpet Network incentivises five main categories of network participant in order to leverage the collective wisdom of the world's data scientists and extract valuable analytics from raw geospatial data.

3.2.1 Organisations

Organisations across the world, whether they are businesses, governments or DAOs, either use geospatial analytics to inform their operations or would greatly benefit from doing so. Financial value enters the Flyingcarpet Network when organisations purchase analytics from Flyingcarpet models via the Models Dashboard or submit a model creation request on the Geospatial Dashboard. Despite Flyingcarpet's complex, back-end processes, organisations purchase analytics using a stablecoin via an intuitive UI that automates token swaps.

3.2.2 Model Investors

Anyone can function as a model investor by staking NTN against Flyingcarpet models. Due to Flyingcarpet's token economics, the value of these stakes rise as demand for a staked model's analytics grows. Furthermore, fees collected across the network are distributed amongst model investors in proportion to the value of their stakes. This is explained further in Section 8.

3.2.3 Geospatial Data Providers

Data providers are companies who provide specific geospatial data required for creating and running Flyingcarpet models. In Section 2, we referred to large satellite imagery providers, however, in the future, the Flyingcarpet Network will accommodate an entire spectrum of data providers, including planes, drones and static cameras. A portion of the NTN (swapped from Nx) spent on model creation and execution is allocated to incentivising data providers.

3.2.4 Data Scientists

Primarily, data scientists compete in Flyingcarpet model creation competitions (see Section 5) by building analytics-extraction models. Numerai's success has shown that with proper incentives, a global pool of data scientists can be brought to bear on any given dataset to produce cost-effective, highly-specific analytics-extraction models. The Flyingcarpet Network will enable data scientists access to rewarding model creation opportunities, without having to work for a centralised analytics firm that captures most of the value that their efforts create.

Data scientists earn a fixed amount up-front when they create a model, in addition to a percentage of the recurring revenue when their models are used.

3.2.5 Human Classifiers

As explained in Section 5, human classifiers play a critical role in annotating both the training and testing datasets that are crucial to verifying the integrity of the models, which thereby ensures that models are accurate and trust-minimised. The job of human classifier will present a remarkable income opportunity for people across the world, particularly in emerging economies. Data entry workers in India currently earn approximately $1,900 USD annually.[9] By working as a human classifier on the Flyingcarpet Network, annotating imagery for model requests worldwide, we envisage that such workers can earn considerably more.

3.3 User Interface

The success of Web 3.0 applications will be due in no small part to attractive and highly practical user interfaces; Flyingcarpet is no different. Therefore, while our underlying architecture and back-end processes might appear complex, these will be elegantly concealed behind front-end abstractions. Where appropriate, the following sections of this paper touch briefly on UI.

4 The Nitrogen (NTN) and Nitrogenx (Nx) Tokens

The Flyingcarpet Network has multiple native utility tokens: one ERC-20 token called Nitrogen (NTN) and one ERC-20 Bonded Curve Token per model.[10] Nitrogen serves a number of different purposes throughout the Flyingcarpet Network, which are elaborated upon below. Meanwhile, Nitrogenx (Nx) is used to purchase analytics from models, and the supply of Nx for each model is controlled by a bonding curve (see Section 8).

4.1 Nitrogen (NTN) Generation

An initial large predetermined amount of Nitrogen (NTN) will be generated and disseminated to all registered data scientists. 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 model competitions, they will not be able to transfer new tokens—data scientists can only transfer tokens that they have previously staked against successful models (tokens that have been returned). The staking mechanism is controlled by a locking period and a fee to enter and exit the bonding curve to avoid arbitrage and price manipulations.

4.2 Model Competitions

As detailed 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 competitions are irreversibly destroyed.

[9] https://www.payscale.com/research/IN/Job=Data_Entry_Operator/Salary
[10] https://medium.com/@simondlr/tokens-2-0-curved-token-bonding-in-curation-markets-1764a2e0bee5

4.3 Model Competition Planning

The Nitrogen (NTN) token is also used by registry candidates who want to add opportunities to the Token-Curated Registry (TCR), as explained earlier. Organizations will often also participate in registry curation as they have a vested interested in which competitions are run. Anyone who holds Nitrogen (NTN) can participate in registry curation with a degree of voting power relative to the amount of Nitrogen (NTN) that they stake in the TCR.

5 The Geospatial Dashboard

The Geospatial Dashboard is the interface through which paying organisations can submit requests for new models. If a model already exists for an organisation's particular needs, they can simply purchase analytics from the Models Dashboard (see Section 9). This section dives deeper into the specific mechanics of how organisations can request new models and how NTN holders can vote on which requests become model competitions.

5.1 Submitting Model Requests

Anyone can submit new model creation requests. When submitting requests, organisations must include precise information about the geographical areas where the model is to be applied (e.g. geographical coordinates of regions) and the geospatial analytics that must be extracted by the model.

5.2 Model Competition Voting

A token-curated registry (TCR) is used by token holders to rank the different options for model creation. These options may be ranked based on viability, potential usefulness and so on. Anyone who holds NTN can curate the model creation options listed on the TCR. The TCR assigns curation rights proportional to the amount of NTN staked by a token holder. Analytics recipients—such as businesses, commodity traders, governments and DAOs—have an incentive to hold NTN token in order to influence which opportunities are ranked highest on the registry and thereby leverage data scientists for their specific analytics needs.

6 The Annotation Portal

Proof-of-Existence (PoE) models that are created through the competition mechanism (see Section 7) are trained and tested using different datasets, which are annotated by human data classifiers. This takes place on the Annotation Portal, which is a Mechanical Turk-like interface that offers human classifiers a small payout for each annotation they complete. Any participant can be a human classifier, including data scientists and model investors. Although this is low-value work, it will represent a significant opportunity for workers in emerging economies.

6.1 Training Datasets

Data classifiers have different incentives depending on whether they are annotating training or testing datasets. Incentivisation of open-source training dataset classification is handled using a bounties system[11]. A preset portion of funds raised for model creation is dedicated to bountying the sourcing of an open-source training dataset. Creating high quality training data is in the interest of the entire

[11] https://gitcoin.com

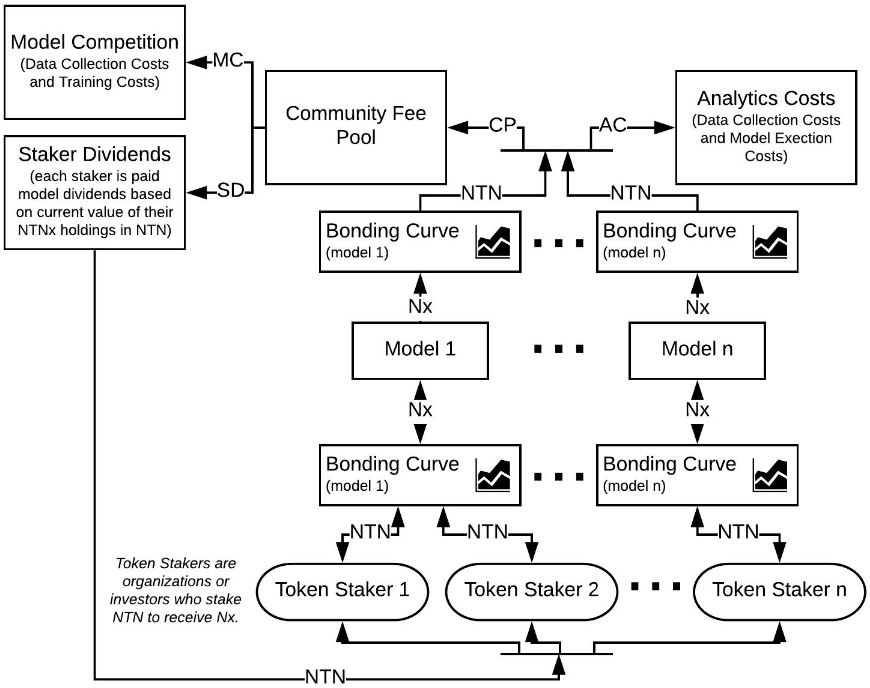
Flyingcarpet community since training datasets are shared by all data scientists creating models. Of course, data scientists may also create and use their own private training datasets to improve their models.

6.2 Testing Datasets

Since 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 when run on the satellite imagery. When submitting subset output solutions, human classifiers must stake a substantial fixed amount of NTN as collateral against the quality and integrity of their manual classifications in case disputes arise (see Section 10).

7 Model Creation Competitions

As outlined in Section 6.2, all NTN token holders may participate in model competition option planning. Machine learning models are created to extract geospatial analytics from raw satellite data. These models are sourced via a model creation competition where all successful data scientists benefit from the rewards. Analytics are made available to businesses via the Analytics API (see Section 10).

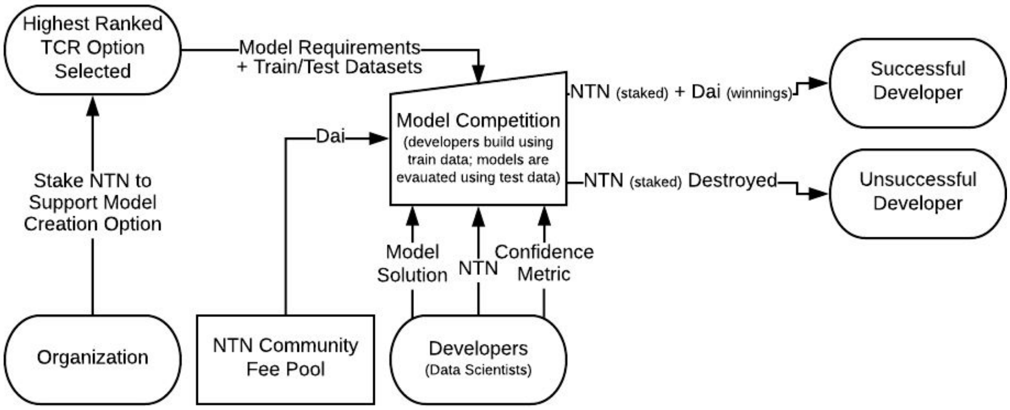


AC = the primary (largest) percentage of model revenue (NTN generated by burning Nx to purchase analytics), used to pay for all costs associated with obtaining the desired analytics; CP = the secondary (smaller) percentage of model revenue, used to fund the community fee pool; MC = the primary (largest) percentage of community pool funds, used to fund future model creation competitions; SD = the secondary (smaller) percentage of community pool funds, used to reward successful community members (token stakers) with recurring dividends.

7.1 Model Creation

Raw geospatial imagery is provided to the Flyingcarpet Network primarily from satellite sources—however models for plane and drone imagery may also be created. Satellite and plane data is provided by highly reputable, global data companies.

If an adequate model does not already exists for the specific analytics, then a new model must be created to extract the desired geospatial analytics. After the raw data has been provided for the specific model, it is annotated, as outlined in Section 5.1. A competition is then run where data scientists create, train and submit models.



The machine learning model competition process flow.

The reward for each model competition is funded via the NTN community fee pool—collected via a small percentage fee taken each time a model is executed. Data scientists are provided with only the model competition 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 NTN tokens are returned. On the other hand, data scientists whose models failed, have their staked NTN token 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.

In addition to receiving a one-time payment, data scientists who create winning models, also receive initial Nx tokens for the model they've created. All of these initial Nx tokens for the data scientist are minted at the price of zero on the bonding curve, thus the bonding curve's price does not begin to increase beyond zero until after this initial token supply.

Finally, after the competition, the testing dataset is made open-source for public scrutiny. Flyingcarpet will integrate with a decentralised arbitration system in order to enable data scientists to raise objections to testing dataset sub-solutions provided by the human classifiers. This is further explained in Section 10.

7.2 Model Use

Once the required raw data has been collected and a model sourced, rich analytics can be extracted for organizations, who can pay directly in Dai (or fiat through an exchange integration). Access to existing models for data extraction are continually available to organizations through our oracles and API. These can be directly integrated into any smart-contract or application and enable access to rich data analytics in near real-time. 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 marketplace, enabling the creation of Flyingcarpet models for specific, targeted Erasure predictions.[12]

Model investors—holders of a model's Nx token—receive royalties in the form of Dai whenever analytics from models they've invested in are purchased by organizations. Due to this revenue stream, model investors are incentivised to buy into models that they believe will produce reusable, generic, geographically-versatile models that extract rich geospatial insights.

7.3 Model Delegate Mining

As noted above, models are stored decentrally with all model computation, including both training and testing computation, takes place off-chain, using a decentralised cloud service such as OpenMined or Golem.[13] We envisage that OpenMined will be more suitable for the Flyingcarpet Network because the service secures and encrypts both models and datasets, thereby enabling both data scientists and data providers to be confident that their intellectual property will not be stolen if they participate in model creation competitions. Importantly, OpenMined does not pass around data to data scientists seeking to train models; instead, "miners" pull the encrypted models and train them locally on their devices. These "miners" are rewarded for their compute power and for how much they improve the encrypted models, which further extends the economic impact of the Flyingcarpet Network.

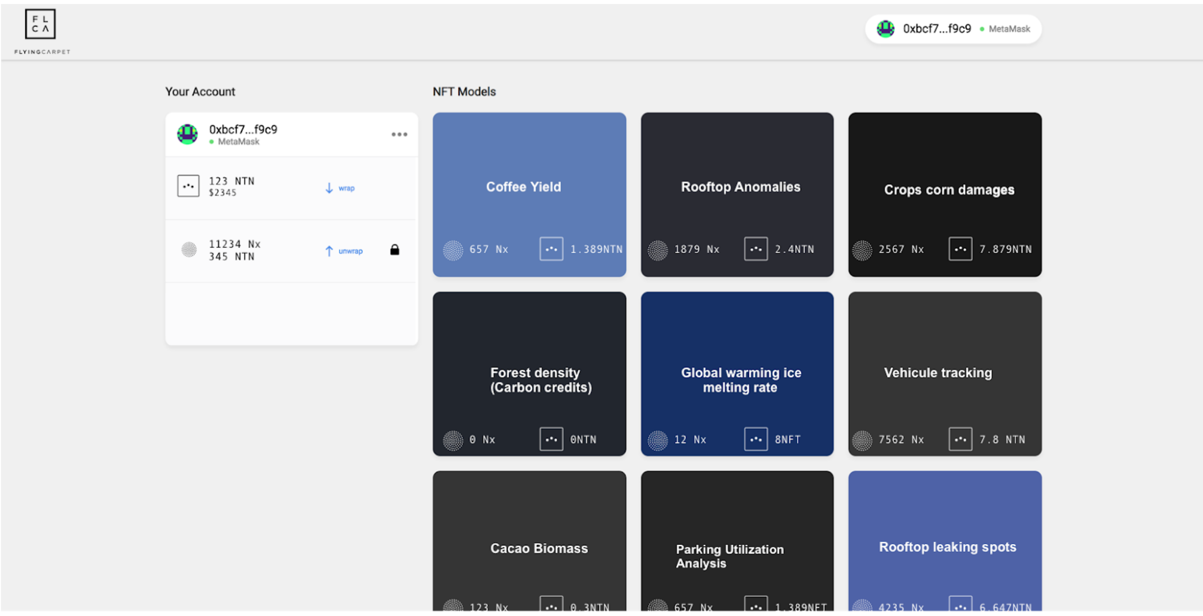
[12] https://medium.com/numerai/numerai-reveals-erasure-unstoppable-peer-to-peer-data-feeds-4fbb8d92820a
[13] https://www.openmined.org/

7.4 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[14] by both Flyingcarpet and the community (e.g. businesses who have particular interests in the development of generalized base classifiers for their use cases).

8 The Models Dashboard & Analytics Pricing

Successful models are displayed on the Models Dashboard, which displays real-time analytics prices. Since each Flyingcarpet model essentially functions as a shop that sells a single product: a specific type of geospatial analytics. To efficiently price these analytics, a mechanism that aggregates demand for the analytics that any given model generates is needed in order to find the equilibrium price. The Flyingcarpet Network uses token bonding curves, which have been pioneered by Simon de la Rouviere, to do this.



The Flyingcarpet models dashboard is composed of all the different models. Users / investors can see different metrics per model: investment, derivatives, bonds and predictions. (Illustration based on https://ox.org)

8.1 Bonding Curves

The premise of a bonding curve is that one token (in this case, NTN) is used to generate another token (in this case, Nx) along a predefined curve, with the latter offering some particular utility (in this case, geospatial analytics) that cannot be efficiently priced with some other mechanism.

On the Flyingcarpet Network, each model on the Models Dashboard is assigned two bonding curves—a buy curve and sell curve—that determine the price of the model's analytics. As more Nx is generated,

[14] Such as Gitcoin

the price of Nx increases (in NTN), in accordance with the bonding curves. To support an upward, long-term Nx price trajectory and to encourage considered investment based on model fundamentals, the sell curve is positioned below the buy curve, such that the cost (in NTN) of buying a stake will always be less than "selling" their Nx into the bonding curve. Furthermore, fees (see Section 8.2) and locking periods are applied when participants buy and sell into the bonding curves to deter arbitrageurs.

Note, however, that there is no participant actually "buying" Nx; instead, Nx that is sold into a bonding curve is burned. Furthermore, as mentioned in Section 5, Nx cannot be exchanged outside of the Flyingcarpet Network.

8.2 Model Investment

Any participant—be they an organisation, data provider, data scientist or just an individual seeking to capture the value of the world's geospatial data—that holds NTN token can invest in models by staking their NTN to generate Nx. Since Nx must be burned by organisations seeking analytics, investors that have staked NTN against an in-demand model will see the value of their Nx holdings increase.

Model investors are rewarded in two separate ways. Firstly, they can stake NTN at a low price on the buy curve (perhaps by staking a new model that has not yet seen significant demand) and then selling back into the sell curve when demand has increased and the value of Nx has increased (in NTN), according the bonding curves.

Secondly, when a model is executed, the required amount of Nx is burned and the corresponding amount of NTN (from the bonding curve) is unlocked and used to pay for the model execution costs, in particular data provision and off-chain model computation. A small fee in NTN is also taken, converted into Dai, and transferred to a community fee pool. Model investors who hold Nx (have staked NTN) earn recurring dividends from the dividend pool whenever models are executed. Each model staker's payout is determined by the following equation:

$$\textit{staker Nx payout percentage} = \frac{\textit{current NTN value of staker's Nx (across all models)}}{\textit{total value of all NTN stakers' Nx (across all models)}} * 100\%$$

Therefore, an investor (Nx token holder for at least one model) earns a reward amount from the community fee pool in proportion to the total value (measured in NTN) of his or her Nx tokens (across all models). Thus, an investor who only holds Nx token for one model that performs extremely poorly (never or rarely executed) will not earn much NTN from the community fee pool.

Due to this incentive structure, token holders not only want the models that they have invested in to be used, they also have a vested interest in the success of all models on the Flyingcarpet Network. These NTN staker dividend payments can also be automatically swapped to Dai, so that rewards are shielded from volatility.

9 The Flyingcarpet Analytics API

Once businesses have burned Nx to purchase analytics, they will access these analytics via the Flyingcarpet Analytics API. The Analytics API will also enable analytics to be programmatically inserted into smart contracts for continual real-time access, which will create immense new opportunities for smart contract and DAO development. This will be achieved through integrating with an existing oracles protocol, such as Oraclize or ChainLink. Traditional businesses will, of course, be able to access analytics via the API as well.

9.1 Data Marketplace Integration

Flyingcarpet oracles and API can be easily integrated into existing data marketplaces, such as Ocean Protocol[15] or prediction markets such as Gnosis[16] or Augur.[17] Models can be executed regularly (on specific intervals and at specific geographical locations), with the resulting analytics sent to integrated data marketplaces. In this way, any given data marketplace can operate as an analytics-hungry organization by continually purchasing and on-selling insights extracted by Flyingcarpet models.

9.2 Existing PoE Models

To use existing PoE models, organizations must purchase and burn the Nx token corresponding to the model they would like to access. When a request is made, data is collected and processed by the specific model (see Section 7). The resulting analytics are then returned to the business via the Analytics API. 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.

10 Dispute Resolution

As outlined in Section 7, Flyingcarpet data scientists can raise objections to the testing dataset sub-solutions via a decentralised arbitration application, such as Kleros. The Flyingcarpet Network will specify a fixed window of time when these dataset objections can be raised; after this period expires, objections will no longer be possible.

In order to raise an objection, a data scientist must stake an amount of NTN token equal to that staked by the human classifier. If a human classifier is found to be correct, then both parties' staked NTN 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 model competition's NTN allocated—from the community fee pool.

11 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.

The dramatically decreasing costs of space technology and transportation have increased the availability of high-resolution satellite imagery. This data is a geospatial goldmine; by 2027, big data analytics from satellite imagery alone will generate an estimated $18.1bn per annum.[18] This sector has already begun

[15] https://oceanprotocol.com/
[16] https://gnosis.pm
[17] https://www.augur.net/
[18] http://www.nsr.com/research-reports/satellite-communications-1/big-data-analytics-via-satellite-2nd-edition/

accelerating rapidly; in 2017 alone, AI-driven Earth-observation startups raised $96m—nearly three times more than in 2016.

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. The rest of this section explores several potentially industry-changing use cases.

11.1 Infrastructure

Flyingcarpet has countless applications across infrastructure, from insurance (see Section 3.3) to construction, due largely to the fact that many inspection processes are currently conducted manually. Rooftop analysis is a particularly illustrative example of how Flyingcarpet can improve existing inspection processes in the infrastructure sector.

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.[19] Insurers are rapidly realising that aerial imagery is a cheaper, safer and more effective method than carrying out manual inspections.

Using Flyingcarpet, an organisation could request that data scientists build an optimum model for identifying roof abnormalities from geospatial imagery. Satellite data from the relevant area is then used by data scientists in the model creation competition. In this way, Flyingcarpet improves all inspection-based processes; from a road survey to an inspection of cargo ships in a port, Flyingcarpet improves existing processes that are currently performed manually or by centralised data analytics firms.

11.2 Agriculture

Geospatial analytics—from both satellites and drones—offer significant agricultural insights. The agriculture industry generates $2.4trn for the global economy each year.[20] 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 geospatial 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.

11.3 Insurance

Flyingcarpet will have potentially industry-changing implications for insurance. The Flyingcarpet Analytics API will drastically improve how traditional insurers manage their loss-earn ratios and help to automate the payout process. Meanwhile, Flyingcarpet Oracles will open up a huge range of on-chain insurance possibilities, including commission-less DAOs (see Section 3.3.4).

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[19] https://techcrunch.com/2017/09/05/betterview-just-raised-2-million-to-analyze-drone-footage-for-insurers/

[20] https://croplife.org/news/agriculture-a-2-4-trillion-industry-worth-protecting/

11.3.1 Catastrophe Risk

Geospatial analytics are a natural 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.[21] These insured costs can range from a strong, single earthquake in Japan ($125m) to seasonal flooding along China's Yangtze River Basin ($1.3bn).

The Flyingcarpet Network can be used to extract analytics that regularly and autonomously map locations before and after catastrophes, which will enable underwriters to manage their loss-earn ratios and provide automated claims to customers. Catastrophe risk modelling is key for property casualty insurance companies when setting insurance premiums. Flyingcarpet will make this process more expedient by enabling insurers to access a global pool of data scientists, which will improve underwriting decision accuracy and better determine when to cap portfolio exposure.[22]

11.3.2 Parametric Insurance

Flyingcarpet is particularly suited to parametric insurance, which are policies that attach predetermined payouts to objective measures, such as a weather event, rather than a specific loss amount. Parametric insurance is commonly used in situations that require rapid payouts, such as when a natural disaster strikes or critical infrastructure is damaged, in order to finance relief and rebuilding efforts.

Currently, policyholders need to place an immense amount of trust in insurers and the parties measuring the parameters of their insurance plan. By using Flyingcarpet, insurers can request highly-specific models for insurance plans that depend on geospatial parameters. Since models are stored decentrally with on-chain proof, they are tamper-proof and trust-minimised. Therefore, parametric policies that use Flyingcarpet's Analytics API can tilt the balance of power in the insurer-policyholder relationship towards the policyholder and will likely reduce the scope for disputes.

Flyingcarpet can take parametric insurance one step further. Trust-minimised Flyingcarpet Oracles can report parametric measures back to the blockchain and thereby enable parametric insurance policies to be hardcoded into smart contracts. This will fundamentally reduce the transactional costs associated with lower-premium plans, such as those held by small-hold farmers in third world countries, which will improve their ability to access insurance.

The Flyingcarpet Network will also open up the market for parametric insurance. In order to offer parametric insurance, insurers presently need to have a relationship with a locally-based claims adjustor. However, by providing insurers with trusted data sources and trust-minimised analytics-extraction models that report on parametric measures, the Flyingcarpet Network means that they are no longer needed.

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[21] http://thoughtleadership.aonbenfield.com/Documents/20180710-ab-analytics-if-june-global-recap.pdf

[22] http://www.ibmbigdatahub.com/blog/enhancing-catastrophe-risk-modeling-insurance

11.3.3 Nano-Parametric Insurance

The Flyingcarpet Network can also facilitate what we have termed nano-parametric insurance, whereby small, distinct geographical items—such as one part of a structure, or very small plots of land, such as one square metre of a crop field—are individually covered by a parametric insurer. This enables damage assessment for an entire structure or field to take place at the "nano" level, which means that policyholders can get paid out for highly specific or localised damage that ordinarily would not trigger a payout from a regular parametric insurance policy.

11.3.4 Commission-less DAOs

A potential bypass of the insurance broker altogether is possible by funnelling claims through commission-less decentralized insurance DAOs.[23] This new incentive structure unlocks enormous value by eradicating brokerage fees, which are often as high as 25%—and sometimes even 50%.[24] 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.

11.4 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 geospatial imagery are limitless. Companies, investors, traders, governments and nonprofit organizations can all benefit from these previously inaccessible analytical models.

12 Complete Use Case Example

This section walks through an end-to-end use case example of the Flyingcarpet network. A global cacao trader, for example, requires detailed yield insights on the coffee production of a one thousand square km area of Columbia. In order to obtain highly accurate estimates, satellite footage will be used to train, test and use the model.

First, using an intuitive UI on the Flyingcarpet dashboard, the energy provider simply requests analytics based on their specific needs. Since no machine learning model currently exists for the analytics that are required, NTN token holders vote on the request by staking NTN to curate a TCR of model competition options.

[23] https://etherisc.com/
[24] https://cass-stephens.co.uk/insurance-broker-commission-disclosure

Eventually, if the community believe that the cacao trader's desired model carries economic potential, a model creation competition is spawned. Data is automatically sourced from Flyingcarpet's satellite providers, and bounties are made for human classifiers to manually annotate the raw imagery for training and testing the machine learning models submitted to the competition. Each dataset consists of a collection of raw data combined with a definition of expected results (e.g. in the case of cacao fields, each image is marked up with the approximate crop yield, etc.).

Once the competition begins, 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). These model competition rewards come from the community fee pool—funded from fees collected when existing models are executed.

After the competition ends, the testing dataset that was used to evaluate the models is decrypted and made public. As described in Section 10, data scientists have a fixed window during which they can raise objections to the testing dataset if the feel that its classifications are incorrect.

Finally, the cacao trader runs the model, via the Flyingcarpet network, to extract the coffee production yield estimate insights they need to make informed decisions about traders associated with the one thousand square km region. Other interested parties can also benefit from this cacao model. For example, crop shipping companies that operate cargo ships to and from South American could use these analytics to make informed bets for or against how future shipping requirements. Additionally, anyone can invest in the future value of the cacao prediction model by purchasing model Nx using NTN. Nx holders for the cacao model can then batch sell their Nx as the price increases up the bonding curve, as well as earn recurring dividend payouts from the use of all network models. This will open up two potential revenue streams across countless industries and use cases for anyone with a even a small amount of capital.

13 Conclusion

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. As Flyingcarpet's decentralised library of machine learning models grows and demand increases for the analytics that they generate, all token holders benefit.

By maximising and aligning incentives for all participants, the Flyingcarpet network enables AI-powered, geospatial analytics from satellite imagery to be extracted and sold to businesses via an 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.