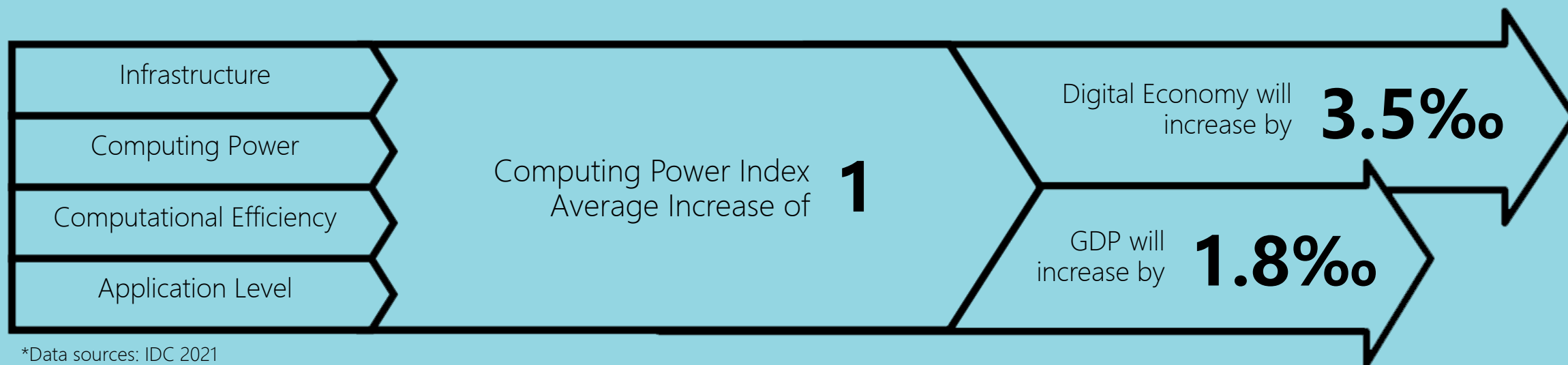


# MatrixAI

**Network As Computers**

**Decentralized Computing Network**

## Computing | An area closely related to the world economy

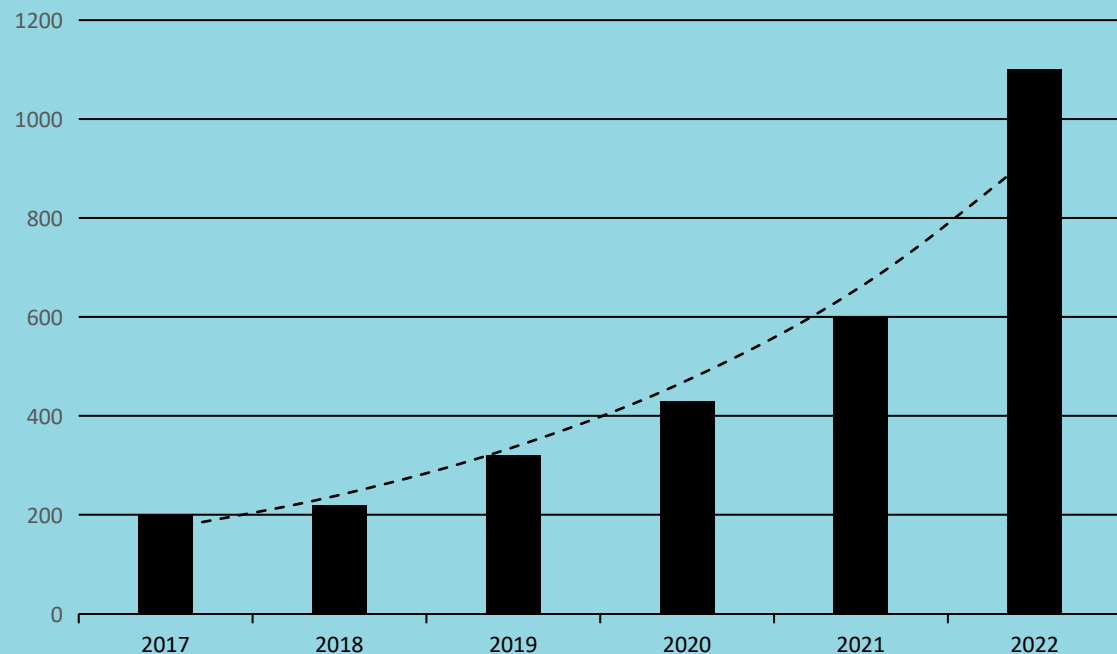


\*Data sources: IDC 2021

From a quantitative perspective, computing power has a significant impact on the macroeconomic development of a country. According to IDC's report, there is a significant positive correlation between a country's computing power index and its GDP/digital economy trends. On average, for the 15 key countries<sup>[1]</sup>, a 1-point increase in the computing power index leads to a 0.35% growth in the digital economy and a 0.18% growth in GDP. This trend is expected to continue from 2021 to 2025.

\*15 key countries: United States, China, Japan, Germany, United Kingdom, France, Canada, South Korea, Australia, India, Italy, Brazil, Russia, South Africa, Malaysia

## Computing Power | Strong market demand

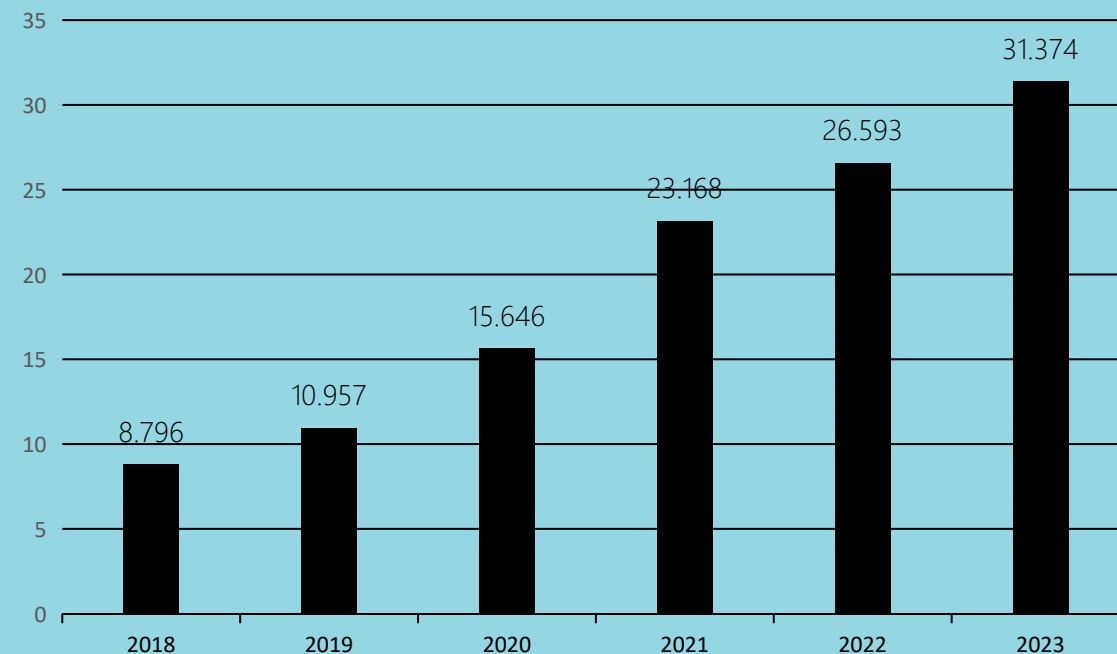


Global computing power scale (EFlops)

**+65%**

Annual Growth

The global computing power scale is maintaining a high-speed and stable growth trend. The rapid rise of fields such as artificial intelligence, scientific research, and the metaverse poses higher demands on computing power. It is estimated that by 2030, the average annual growth rate of the global computing power scale will reach 65%.



Global computing power market size (trillion US dollars)

**\$31.3B**

2023

In 2021, the global computing power network market reached a scale of \$23.168 billion, with a year-on-year growth of 48.08%. The computing power network has become a new focus worldwide, and it is expected that the market size will further increase to \$31.374 billion by 2023.

## Problem | Restricted AI development

“Computing power has become a key constraint for further development of artificial intelligence”



### High computing costs

Ordinary PC is unable to meet the requirements of complex computing tasks. If GPT-3 is used with V100, it would require 355 years of training. Building cloud computing infrastructure requires extremely high costs

**4 million USD:** The estimated cost of one training session for ChatGPT

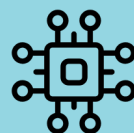
**0.7 million USD:** The estimated daily hardware operating cost for ChatGPT



### Inefficient resource utilization

High-end servers are generally scattered, and idle resources are not fully utilized

**20-30%:** The global computing resource utilization rate



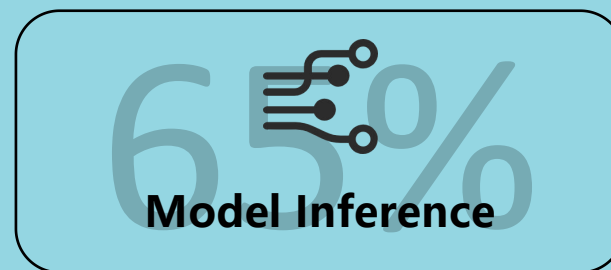
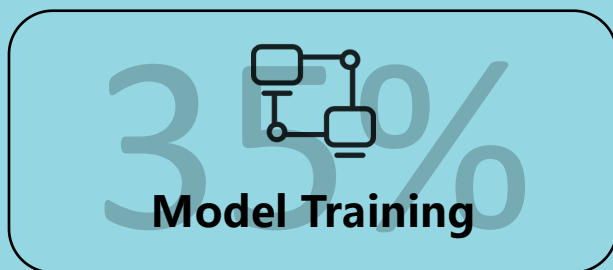
### Giant monopoly

Indeed, highly centralized resources and data monopolies give monopolistic companies significant control over data and pricing power for computing power. This can create barriers to entry for smaller players and limit competition in the market

**61% Gross margin:** AWS offers commoditized compute hardware

## MatrixAI | Web3 Computing Power Network

MatrixAI includes a **protocol for integrating and scheduling computing power**, as well as a **peer-to-peer trading market**. Its main use case is to allocate computing tasks to idle computing power, and providers receive economic incentives by submitting proof of calculation.



MatrixAI

MarketShare DeviceMy OrdersFaucet

### Computing Power Market

Filter

ANY GPUs

ANY GPU

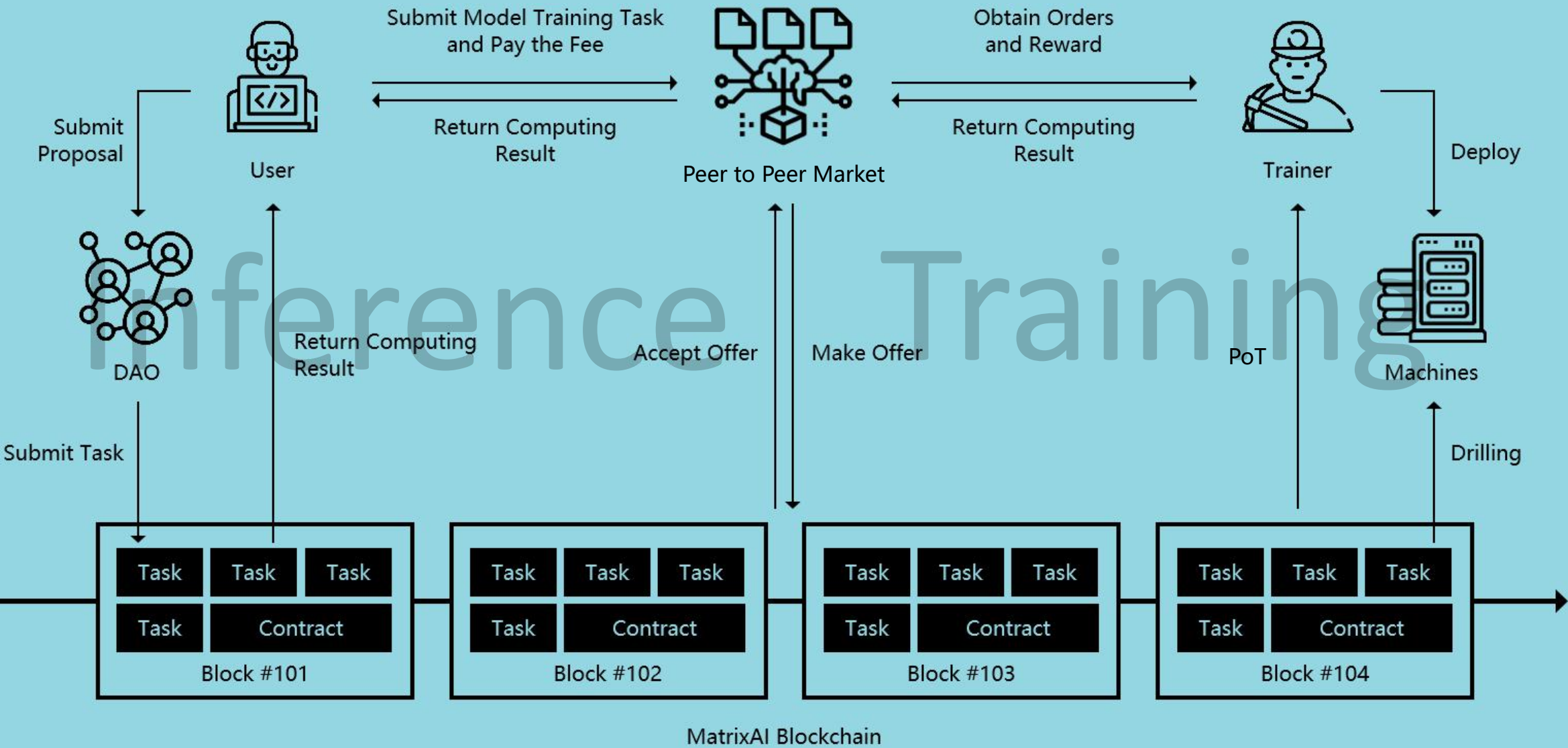
ANY Region

Auto Sort





reset

Provider	Configuration	Price (h)	
<div>0x982s02...gh9l220</div> <div>#30294870</div> <div>98.54% Reliability</div> <div>92 CPS</div> <div>Asia</div>	<div>1x RTX 4090</div> <div>2x AMD Ryzen Threadripper PRO 5955WX 16-Cores</div> <div>44.5 TFLOPS</div> <div>24 GB RAM</div> <div>286 GB Avail. Disk Storage</div> <div>Max Duration: 12h</div> <div>583 Mbps1623 Mbps</div>	<div>15.03</div>	<div>Select</div>
<div>0x982s02...gh9l220</div> <div>#30294870</div> <div>98.54% Reliability</div> <div>74 CPS</div> <div>Europe</div>	<div>8x A100 PCIE</div> <div>16x Core™ i5-10400F</div> <div>44.5 TFLOPS</div> <div>24 GB RAM</div> <div>286 GB Avail. Disk Storage</div> <div>Max Duration: 12h</div> <div>583 Mbps1623 Mbps</div>	<div>18.15</div>	<div>Select</div>

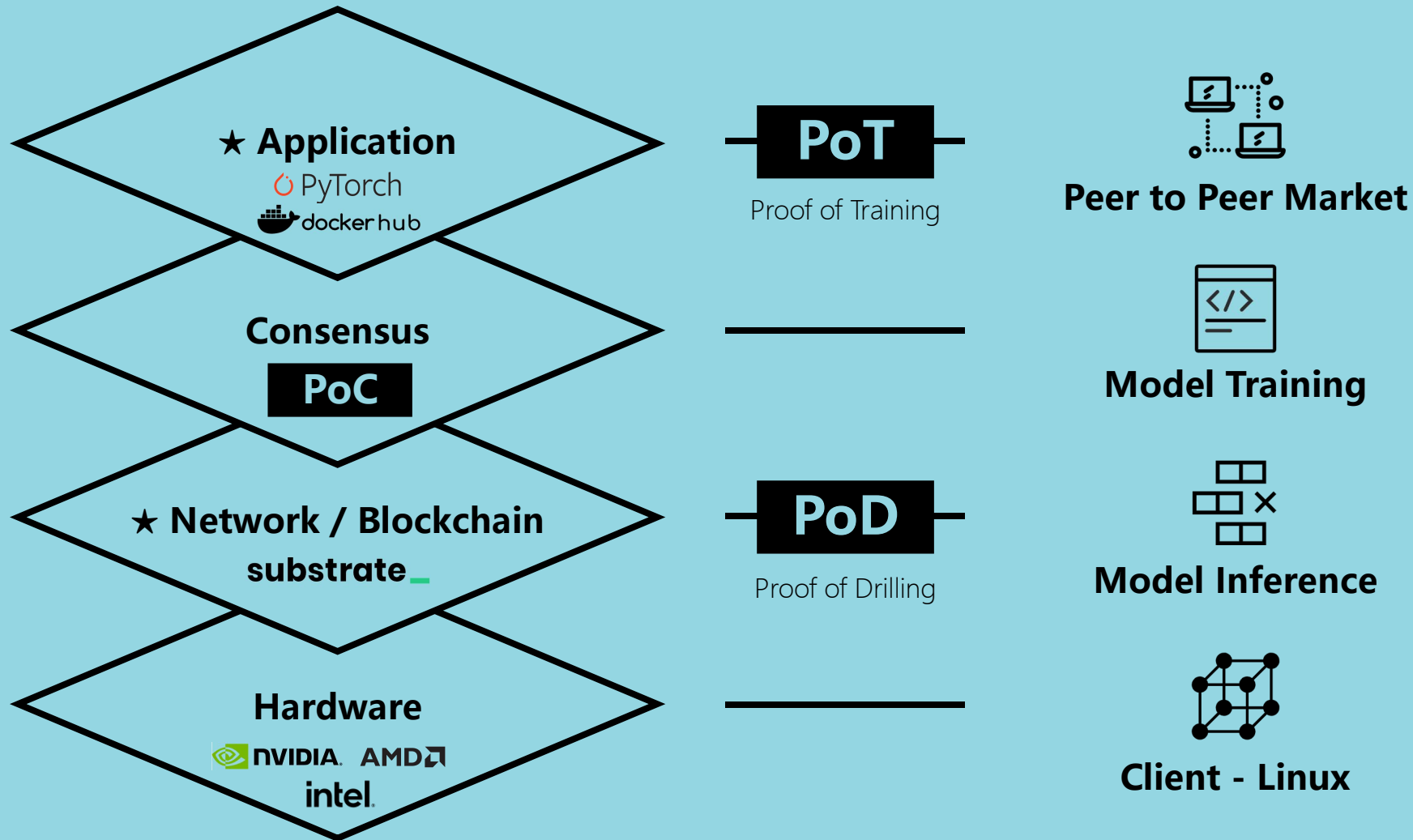
Bussiness Model | Public, Transparent and Direct



# Computing Network | There is an increasing number of Players

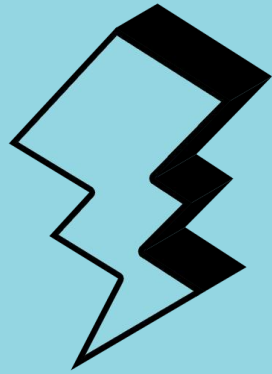
	Feature	Introduction	Investment
 2022.4	<ul style="list-style-type: none"> <li>- Early &amp; Testnet</li> <li>- Apply to access/supply machines</li> <li>- Expected cost reduction by 3x</li> <li>- No economic model</li> <li>- Calculate routing, scheduling, and transactions</li> </ul>	<p>exaBITS is a project within Harvard Innovation Lab Incubation Program, aiming to build a Web3.0 infrastructure with zero downtime, low costs, and infinite computing power. The market will have access to various artificial intelligence-related services and resources, including computing services, data storage, and model-as-a-service (MaaS). It can partition large-scale AI models and run them on extremely weak GPUs.</p>	<p>Harvard Innovation Labs</p>
 2016.9	<ul style="list-style-type: none"> <li>- Mainnet V8</li> <li>- Connects cloud resource sellers with cloud resource buyers</li> <li>- Computing, Application, data could be traded</li> <li>- Task Orders</li> <li>- TEE</li> </ul>	<p>iExec's technology relies on Ethereum smart contracts and enables on-demand provision of high-performance computing services through virtual cloud infrastructure. It allows for on-demand provision of off-chain computing services and datasets, and verification is achieved through the PoCo consensus protocol. iExec also provides other products to enhance ownership and privacy protection, including the Oracle Factory, iExec SDK, and confidential computing.</p>	<p><b>\$12M:</b> 2017.4.19 ICO</p>
 2020.5	<ul style="list-style-type: none"> <li>- Mainnet</li> <li>- Cloud virtual machine rental</li> <li>- Customizable device parameters</li> <li>- Access to computing resources without permission</li> <li>- Delegated proof of stake consensus mechanism</li> </ul>	<p>Cudos is a Layer1 blockchain that focuses on delegated proof of stake. Its vision is to achieve on-chain accessible decentralized computing. The design of its network separates consensus from execution to ensure security, decentralization, and permissionless access to high-performance computing. The design of the Cudos network separates consensus from execution to ensure security, decentralization, and permissionless access to high-performance computing.</p>	<p><b>\$600K:</b> 2019.12.4 Seed Round - Outlier Ventures</p>
 2019.6	<ul style="list-style-type: none"> <li>- Early</li> <li>- Probabilistic Learning Proof</li> <li>- Distributed Parallel Computing</li> <li>- Model Data Privacy Protection</li> <li>- No Economic Model Currently</li> </ul>	<p>The Gensyn protocol will become the underlying layer for machine learning computations, similar to the Ethereum platform for executing smart contracts. It aims to be a large-scale and cost-effective computing protocol for global deep learning models. It enables anyone to use a self-organizing network that includes all existing computing resources to train machine learning models for any task.</p>	<p><b>Over \$50m:</b> a16z leads the investment, with participation from CoinFund, Canonical Crypto, Protocol Labs, Eden Block</p>

## Difference | Value, Application Scenarios, Layer





## Benefit | Efficient, Lower Costs, Fair



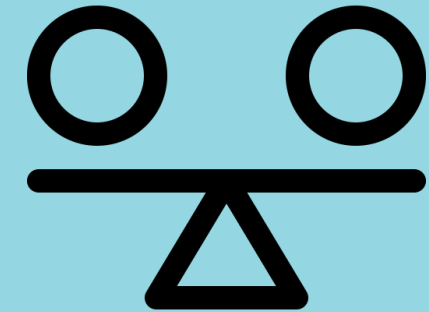
### More Efficient

- Users can instantly trade with crypto and select a model to start training in minutes
- Orders are settled almost in real time



### Lower Costs

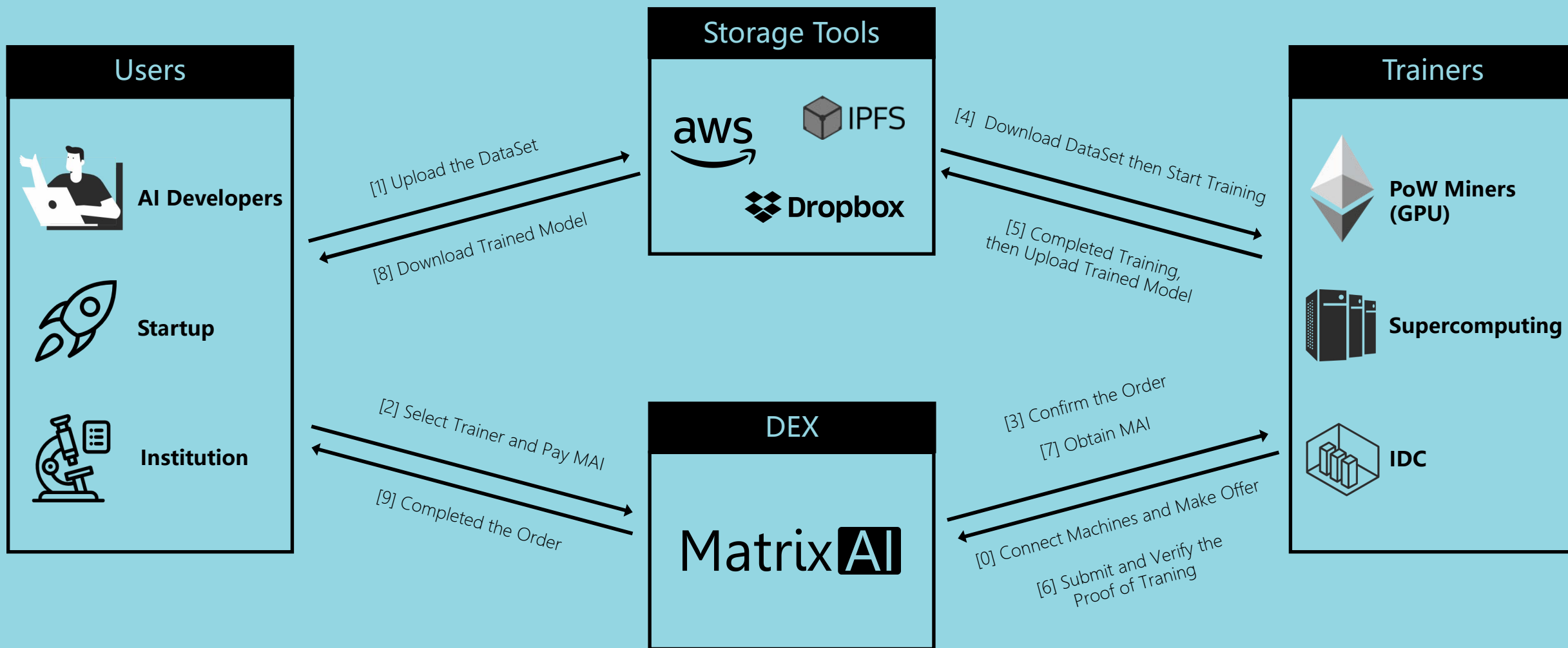
- Introduce bidding from different providers to form price competition. Expected cost is reduction of 75% to 90% or more
- Low access threshold, users can share idle computing power, it means lower costs



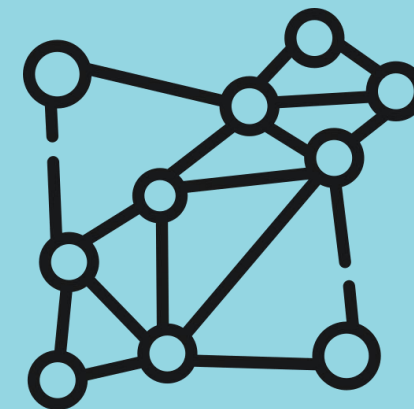
### The Principle of Fair Incentives

- Incentives are distributed based on the contribution of the participants, rather than distributing profits through resource monopolies

## User Case | Connect Users and Trainers



## Solution | Technical Innovation



### DEX for Computing Power

By connecting idle computing resources to the MatrixAI Network, trainers can earn economic benefits from their underutilized resources. Users, on the other hand, can send their computational tasks to trainers through an open and transparent marketplace.

### Proof of Compute

After completing the computational tasks, trainers can submit the generated PoT or PoD to the blockchain network. The network can randomly assign miners to validate the proof, ensuring that trainers have genuinely and effectively completed the assigned tasks.

### Computing integration protocol

The Computing Integration Protocol aims to connect computing facilities with varying geographical locations and configurations to increase the overall computational capacity of the network. The network can leverage the combined power of these facilities, enabling more efficient and scalable computations.

## Roadmap | Aggregate Computing Resources

**Q3****2023**

- Computer Power (P2P)Market Launched ☒
- Client v1.1 Updating: Support Docker Image ☒
- Completed MatrixAI Litepaper ☒

**Q4****2023**

- Economical Whitepaper Release
- Mining Machine Testing
- Developer Communication
- Grants Application

**Q1****2024**

- Computing Integration Protocol
- Client v1.2 Updating: Support More Model

**Q2****2024**

- Mainnet(Computing Pool) Launched
- MatrixAI Virtual Machine Launched

Litepaper | Upcoming Release

MatrixAI

MatrixAI Litepaper

Contract Lab // Released v0.1 // 2023-07

Abstract

The progress of AI heavily relies on large-scale training computation, but the high resource requirements pose barriers to access and impede progress. Current solutions for computational resources are monopolistic, expensive, and impractical for large-scale AI. Decentralized computing services offer advantages such as cost reduction, privacy protection, and innovation opportunities. This paper introduces MatrixAI, a decentralized AI computing marketplace that aggregates idle computing resources worldwide. MatrixAI aims to be the AI computing resource layer network of the Web3 era, supporting diverse scale requirements and breaking centralized monopolies. By empowering computing suppliers and providing cost-effective solutions, MatrixAI shapes the future of decentralized computing and fosters AI innovation.

1 Introduction

1.1 Background

In the past five years, many significant advancements in deep learning have been achieved through the utilization of increasingly large training computation [2,3]. Such large-scale training is accomplished by simultaneously employing hundreds or thousands of specialized accelerators with high internal chip communication bandwidth, such as Google TPUs, NVIDIA A100 and H100 GPUs, or AMD MI250 GPUs. These accelerators are utilized for several weeks or months to compute thousands or millions of gradient updates. Consequently, the tremendous resource requirements involved in constructing these foundational models pose significant barriers to accessing them, and without a means to capture value while sharing resources, it could potentially lead to stagnation in AI progress.

Currently, the solutions available for providing computational resources are either monopolistic and expensive or impractical due to the complex computations required for large-scale AI. Meeting the ever-growing demand necessitates a cost-effective utilization of all available computing resources.

The present challenge lies in the limitations imposed by the asymptotic progress of microprocessor performance on the computational resources themselves, compounded by chip shortages resulting from supply chain and geopolitical factors.

On the other hand, the average utilization rate of global cloud computing data centers has consistently remained low, indicating the presence of a substantial amount of idle computational resources. Furthermore, with the continual rise in computing power of consumer-grade devices, there is untapped potential in the form of idle computing resources from personal computers, servers, and mobile devices used by individuals and businesses. Additionally, decentralized data transmission and storage infrastructures like IPFS, Filecoin, and Storj are constantly improving.

1.2 Motivation

The catalyst for each wave of technological innovation is often the transformation of something expensive into something affordable enough to be wasteful.

Currently, in the field of physical infrastructure, there is a dominant market controlled by vertically integrated giants such as AWS, GCP, Azure, Nvidia, Cloudflare, Akamai, among others. These companies enjoy high-profit margins within the industry. This situation results in high computational costs for new entrants in the AI field, particularly in the LLM domain, which hampers the development and widespread adoption of AI technologies. However, decentralized computing services offer numerous advantages, including decentralized resources, elasticity and scalability, cost reduction, privacy protection, high reliability, as well as opportunities for innovation and collaboration. We firmly believe that decentralized computing services will be the key to overcoming the current high cost of computational power, making it affordable and accessible, thus opening the doors to technological innovation in the AI industry and paving the way for the future of the AI era.

In order to achieve this goal, we have taken the first step

by establishing a decentralized AI computing marketplace called MatrixAI. Our aim is to aggregate idle AI computing resources from around the world. The vision of MatrixAI is to attract global computing suppliers to participate in the network through a fair and transparent incentive mechanism, thereby creating a vast pool of idle computing resources. We envision MatrixAI as the AI computing resource layer network of the Web3 era, providing support for small-scale AI computing services and high-performance computing clusters to meet diverse scale requirements.

MatrixAI is dedicated to breaking the current centralized monopoly, bringing innovation and progress to AI applications across various industries, and promoting greater openness and sustainability in AI computing services. We firmly believe that through the efforts of MatrixAI, computing suppliers worldwide will be able to unleash their full potential, while computing demanders will gain access to more flexible, efficient, and cost-effective AI computing solutions. We look forward to working with you in shaping the future of this promising decentralized computing field.

**2 Goals**  
As a decentralized AI computing infrastructure, MatrixAI is committed to achieving the following goals:

**2.1 More Economical Supply**  
Providing Input Opportunities for Hardware Suppliers to Become Service Providers. It establishes a marketplace where anyone can join as a "trainer" and exchange their CPU/GPU computing power for economic rewards, thus introducing competition in existing services. While companies like AWS traditionally enjoy a 15-year lead start in terms of user interface, operations, and vertical integration, MatrixAI attracts a new user base that cannot accept pricing dictated by centralized suppliers, aiming to serve a price-sensitive demographic.

**2.2 Benign Subsidy Mechanism**  
Creating a Competitive Market to Reduce Customer Payment Costs. In comparison, AWS EC2 instances approximately 95% profit margin and a 15% overall profit margin to sustain its operation. This value incentivized rewards provided by the MatrixAI network serve as a novel source of income. This incentive mechanism is designed to attract idle computing power providers to join the network, while also having the opportunity to earn additional income by participating in computational tasks. Such motivation will increase competition among computing power providers, driving them to offer more competitive prices and high-quality computing resources. Therefore, by introducing idle computing power providers and incentive mechanisms, the computing power

trading market can achieve supply-demand equilibrium and drive competitive reductions in computing power prices.

**2.3 Verifiable Computing Power**  
The verifiability of computing power within the network is a crucial safeguard for the safety and transparency of the computing power trading market. This characteristic ensures fairness and trustworthiness in computing power transactions. On one hand, honest computing power providers will receive more reasonable economic rewards as their provided computing power can be accurately verified and assessed. This encourages computing power providers to offer high-quality computing power services and establish a good reputation. Furthermore, in order to ensure that computing power buyers can obtain more valuable services as references, the computing power trading market needs to disclose the real computing power situation of each computing power provider. This can be achieved through open verification mechanisms or third-party audits. The transparency of the computing power providers' real computing power situation helps computing power buyers make informed decisions and choose the computing power resources that best suit their needs. Such transparency also helps prevent false advertising in fraudulent activities, thereby maintaining the stability and reliability of the entire computing power trading market.

**3 Design**  
**3.1 Role and Architecture**  
MatrixAI Network is a decentralized AI computing infrastructure based on Substrate [1]. It encompasses various roles within its ecosystem.

**3.1.1 User**  
Users with Training Model Requirements.

**3.1.2 Trainer**  
Anyone user with idle computing power resources can join the MatrixAI Network as a trainer without any barriers to entry. Trainers, as consensus nodes within the network, can earn stable rewards by contributing valid computing power. Valid computing power can be accumulated through two categories:

- **Drilling:** Accomplishing measurable, computationally verifiable tasks assigned by the network. Trainers can voluntarily process such tasks upon joining the network. These computational tasks are released by projects collaborating with the MatrixAI Network community. Specifically, real-world practical applications such as performance-related tasks fall within the realm of machine learning

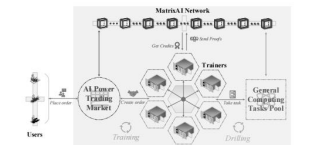


Figure 1: System Architecture of MatrixAI

and can be used to estimate the trainers' actual computing power. Additionally, due to their own independence, these tasks can be easily divided and verified, making them suitable for machines with varying hardware configurations.

• **Training:** By listing computing power resources for sale on the computing power trading market, trainers enter into commitments with users and complete the intended model training. Trainers who join the network have the flexibility to list their computing power resources on the computing power trading market at any time. Before initiating an order and determining the pricing, trainers can refer to the actual conditions of the computing power market. When users select training machines, they can browse through the reported by hardware configuration information of the machines, as well as their historical valid computing power values as references. Once the market is finalized, trainers download the required data from the location specified by the user and proceed with model training as instructed.

**3.2 Proof of Hashrate**  
Proof of Hashrate (PoH) is similar to Bitcoin's Proof of Work in the sense that both rely on the workload of consensus nodes to compute for block generation within each epoch. However, there is one notable difference. In PoH, trainers do not mine blocks; instead, they calculate the hash of their valid computing power values to generate a valid proof. Additionally, PoH incorporates the VRF (Verifiable Random Function) algorithm [10] to hash the valid computing power value of each trainer with the weight

of the VRF. Trainers with higher computing power values have a higher probability of generating a random number that meets the criteria, thereby gaining block generation rights and associated rewards.

**3.3 Computing Power Evaluation System**  
The computing power evaluation system is the cornerstone of the PoH consensus mechanism, ensuring the confidentiality and transparency of the computing power trading market. The computing power evaluation system will dynamically assess the computing power of each trainer, represented numerically as the effective computing power value. The evaluation criteria are based on the quality and quantity of completed tasks. Drilling and Training tasks in the trainers' historical records. In incentive trainers to contribute more computing power resources to the network and complete a greater number of computational tasks. PoH utilizes the effective computing power value as the VRF weight for each task. Trainers with higher computing power values will have a higher probability of obtaining block generation rights and associated rewards. Given that the hardware configurations of trainers are not externally provable, it is challenging to directly rely on an externally provided hardware specifications as trainers set their prices. To provide users with more valuable services for reference, the computing power trading market will publicly disclose the effective computing power value of each trainer. The computing power evaluation system calculates the effective computing power value separately for Drilling and Training tasks, denoted as  $T_{DGP}$  and  $T_{TGP}$ , respectively. Their relationship can be expressed as  $T_{DGP} \times 0.4 + T_{TGP} \times 0.6 \times T_{DGP}$ .

**3.3.1 Definition of Computing Power Value**  
To make computing power resources measurable, we have designed a set of rules for quantifying computing power values. Under these rules, the minimum valid computing power value is defined as "1", which represents the amount of CPU core required to execute the Whetstone benchmark test at a rate of 1,000,000,000 operations per second (1,000,000,000 ops/s). For example, if a machine has a computing power value of 200, it indicates that it has performed computational tasks equivalent to 10 full days of working process and GPU benchmarks computer (including both Drilling and Training tasks).

In MatrixAI Network, two computing power values are maintained:

- **Real Computing Power Value:** The sum of computing power values obtained by a trainer across a period of time.
- **Effective Computing Power Value:** The average computing power value obtained per day over a certain period of time. This average value is reduced by half every week.

**3.3.2 Drilling Scoring Rules**  
Drilling tasks are released by collaborative projects within the MatrixAI Network community. Each task is assigned a difficulty level by the collaborating project and is validated by the community. The difficulty level is measured in terms of computational power required (represented by the algorithmic complexity or workload). Therefore, the scoring rule for  $T_{DGP}$  are as follows:

$T_{DGP} = \frac{\text{Task Difficulty}}{\text{The Number of Tasks}}$

**3.3.3 Training Scoring Rules**  
Training tasks are assigned to trainers based on their acceptance. The scoring rules for  $T_{TGP}$  are similar to those of  $T_{DGP}$ , as they are determined by the difficulty of the task. However, the difference lies in the fact that the difficulty of  $T_{TGP}$  tasks is estimated based on the total number of floating-point operations required for the model training.

**3.4 Proof of Drilling**  
The design of PoH aims to verify whether trainers have faithfully completed Drilling tasks and gain from the  $T_{DGP}$  rewards. The basic principle of PoH verification is to achieve consensus by having multiple trainers complete the same task and return the same work units. If they all reach a consensus, the computational power will be calculated, and all trainers will receive the same amount of credit, regardless of their hardware conditions.

On the contrary, if multiple trainers produce different results for the same Drilling task, all participating trainers will lose the corresponding computational power value.

**3.5 Proof of Training**  
The essential requirement for model training outsourcing services is to ensure the authenticity and reliability of the training process. In a decentralized computing network, users should not blindly trust that the training providers will perform their work faithfully. On the contrary, trainers often violate agreements and commitments in the pursuit of profit. For instance, trainers may engage in arbitrary behavior, deviating from the required training process and providing users with erroneous model data.

In the crypto world, we typically adhere to the principle of "don't trust, verify".

For AI, proposed Proof of Learning (PoL) inspired by research on Proof of Work and verifiable computation [4]. PoL utilizes random checks from the gradient-based optimization process to construct a certificate of work completion, providing evidence that the training party has performed the necessary computational work to obtain a set of model parameters correctly.

Zhang et al. identified the vulnerability of PoL to "subverted output" and demonstrated both theoretically and empirically, their ability to generate an effective proof at significantly lower cost than what the prover would require [1]. Building upon PoL, Zhang et al. introduced a training reliability scheme in 2023, leveraging intermediate checkpoints saved during the model training process to create a coherent chain of models as irrevocable certificates. [1]

Shaoqi proposed a lightweight activity logging strategy based on chip firmware, enabling monitoring of the chip's behavior [15].

Building on the aforementioned approaches, we have conducted further in-depth research and introduced Proof of Training (PoT). The principle behind PoT is to validate whether the intermediate checkpoints generated during the model training process align with the resulting model output through cryptographic comparisons, such as verification accuracy and parameter distribution divergence.

With the support of PoT, the training party only needs to perform model initialization and sequentially save the checkpoints from each training round as a coherent proof bundle during the regular model training process. Anyone who checks the proof bundle can act as a verifier. Utilizing a series of validation algorithms, which we refer to as the "full-proof index", we can verify whether the training party has faithfully completed the model training.

The "full-proof index" consists of the following six verification conditions, and only when all conditions are satisfied, the verification is considered successful.

- The monotonicity of verification accuracy: Given a validation dataset  $D_{val}$  that is similar to the training dataset, the verification accuracy of each checkpoint on  $D_{val}$  should be monotonically non-decreasing.

- **Parameter distribution continuity:** Assuming the model is trained with a sufficiently small learning rate, for any two adjacent checkpoints  $C_i$  and  $C_{i+1}$ , the  $L_2$  norm of the weights in all layers should satisfy a certain condition.
- **Initial parameter distribution:** The parameters of the initial model should follow the standard Gaussian-Matern (SGM) distribution. Given the initial model  $C_0$ , the weights in all layers should satisfy a certain condition.
- **Independence of initial parameters:** The parameters of the initial model should be independent. For the weights in the initialization layer, if we consider two different parameters  $w_i$  and  $w_j$  as random variables, their covariance should be 0.
- **Monotonicity of weight distance:** Assuming the model training converges properly, the distance between consecutive checkpoints and the converged model should monotonically decrease to zero.
- **Final distance between initial and converged models:** Assuming the deep neural network model is sufficiently complex, the distance between the converged model and the initial model in the same model class is likely to be much smaller compared to the distance between the converged model and other randomly initialized models.

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## Core Team | Extensive project experience in AI and WEB3



### Dr.Jerry

Technical Scientist

- Holds a Ph.D. degree with a focus on research areas such as information security, blockchain, etc.
- Senior AI expert
- Has extensive experience in large-scale projects related to federated learning and privacy-preserving computation
- Formerly worked at a leading blockchain company



### Miles

Technical Expert

- Computer Technology Master, focus on blockchain, distributed storage, and attribute-based encryption
- Has published 3 SCI papers and holds several patents.
- Over 5 years of project management experience
- Worked for a leading blockchain company, leading the research and development of Web3 projects



### Han

Product Manager

- EMBAer
- Senior blockchain product expert
- Over 6 years of blockchain product management experience
- Worked in top blockchain company, public chain and crypto currency exchange
- 2022 Polkadot Winter Hackathon 1st Place
- Completed Web3 Foundation Project



### Thirteen Chen

Smart Contract Developer

- Has extensive experience in distributed systems and smart contract development
- Previously worked as a senior development engineer at a well-known blockchain company and participated in AI-based smart contract development projects



## Backer | Active groups in the Web3

L|D CAPITAL

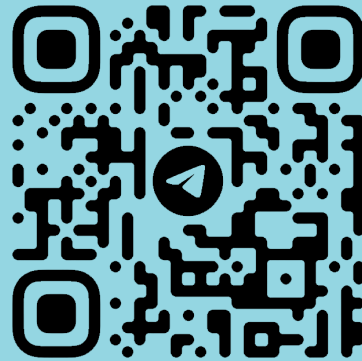
 parity

aws

 Google Cloud

# Thanks !

We are looking for investors  
to accelerate the implementation of AI infrastructure era together



Matrix**AI**

Contact us

**Miles@matrixai.cloud**