# Blockchain-Orchestrated Machine Learning for Privacy Preserving Federated Learning in Electronic Health Data

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1 - ConsenSys Health
2 - Imperial College London
3 - Thomas Jefferson University
4 - Microsoft Corporation
* - Presenting

# What is Decentralized AI?

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Integration of public and private **Blockchain**, **Privacy-in-Depth**, and **Decentralized AI**

**Decentralized Apps** (“dApps”)
*Web3 User Experience*

**Optional Tokenized Assets**
*Secured and Transferred*

**Smart Contracts**
*Secure Automation Across Organizational Boundaries*

**Blockchain Networks**
*Public, Private, and Hybrid*

## Privacy-in-Depth

- Zero-Knowledge Proofs (ZKPs)
- Trusted Execution Environments (TEEs)
- Secure Encrypted Virtualization (SEV)
- Blind Computation
- Verifiable Computation
- Secure Multi-Party Computation
- Differential Privacy
- Homomorphic Encryption
- Quantum-Resistant Encryption

## Decentralized AI

- Federated learning in blockchain networks
- Intelligent agent-based automation
- Optimization w/agent-based simulation
- New paradigm in training data provenance

Web2: Today’s Mainstream Modern Web

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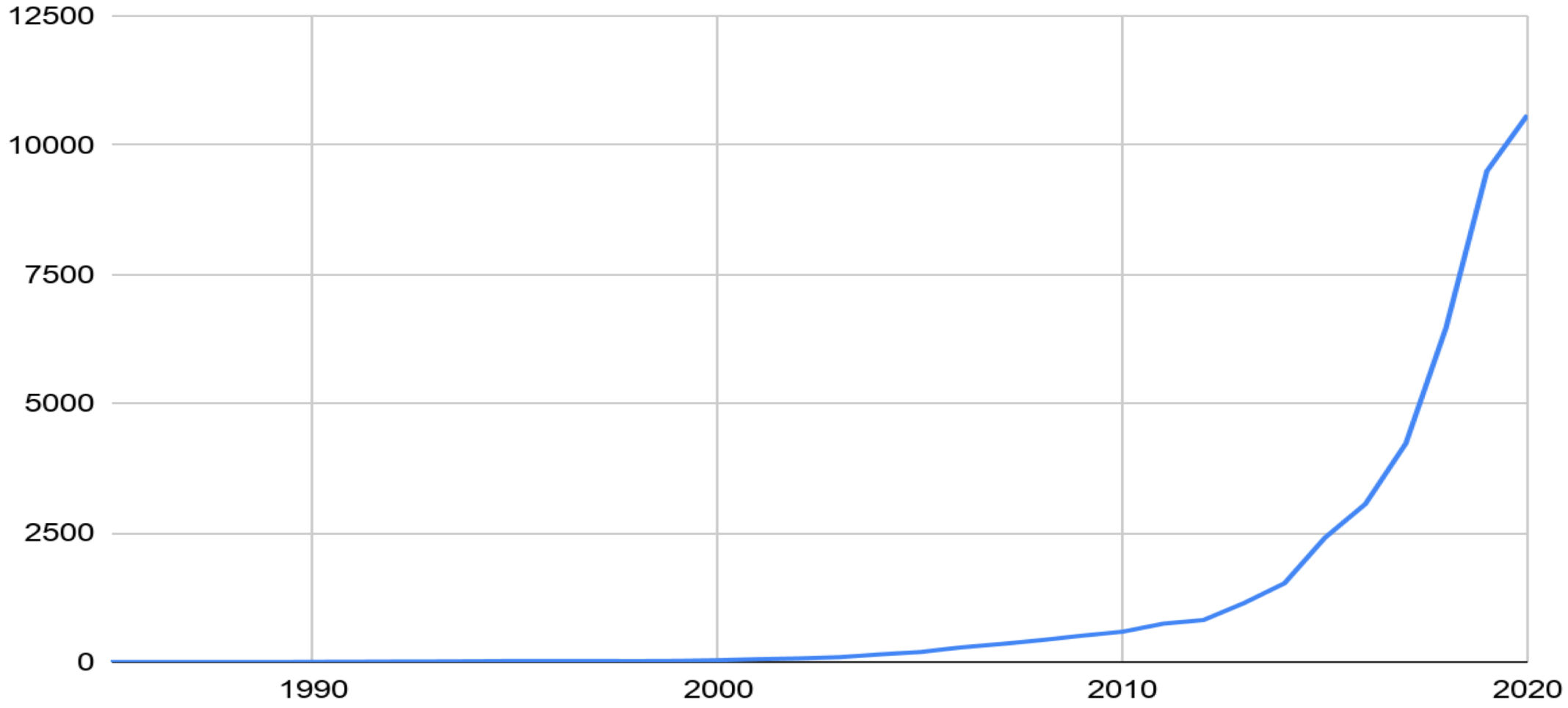
# Machine Learning for Medicine - “machine learning” results by year in PubMed (medical literature database)



# The PHI Readiness Framework

## PHI = Protected Health Information

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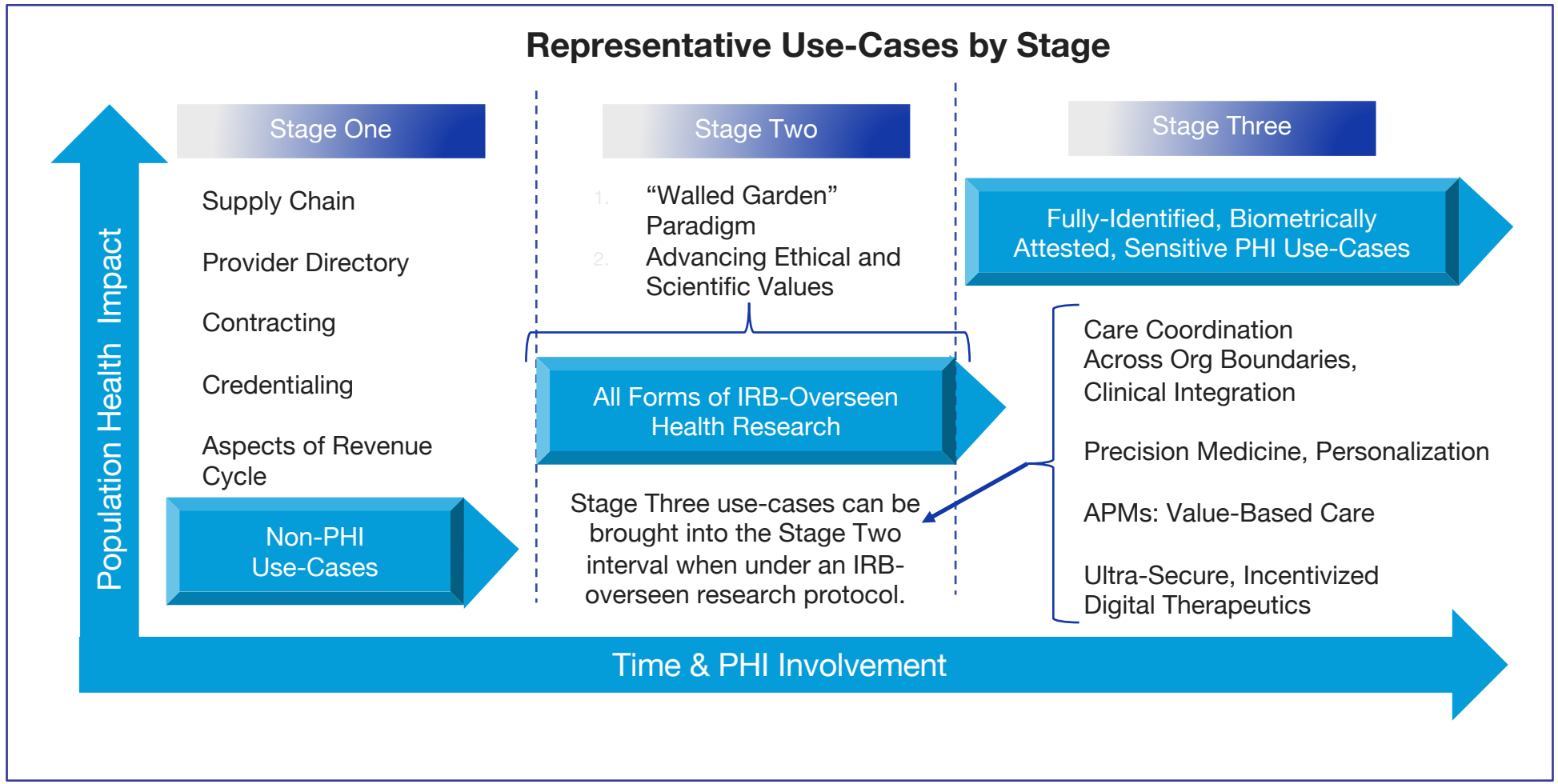

# Two Families of *Converging*, Emerging Technologies

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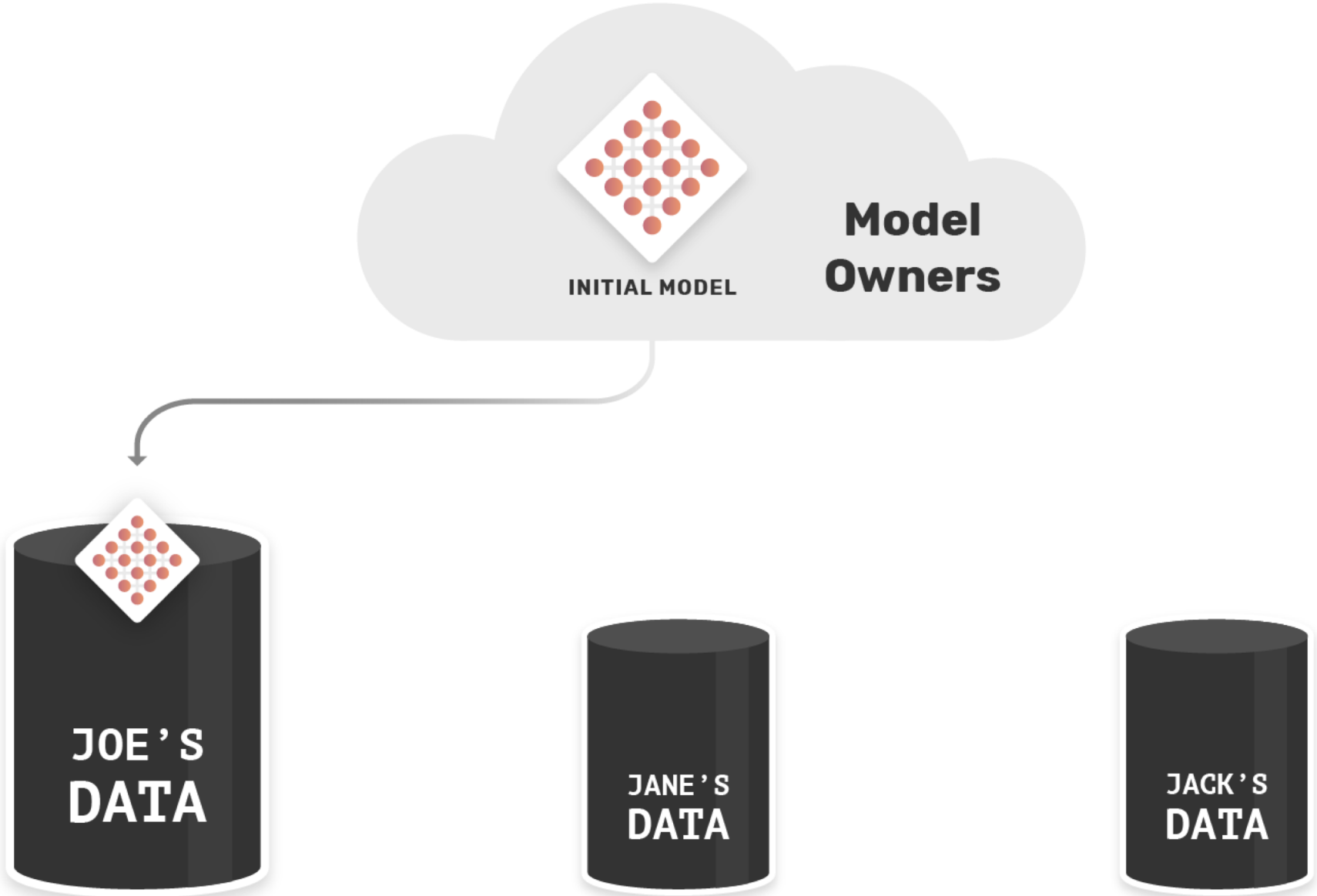
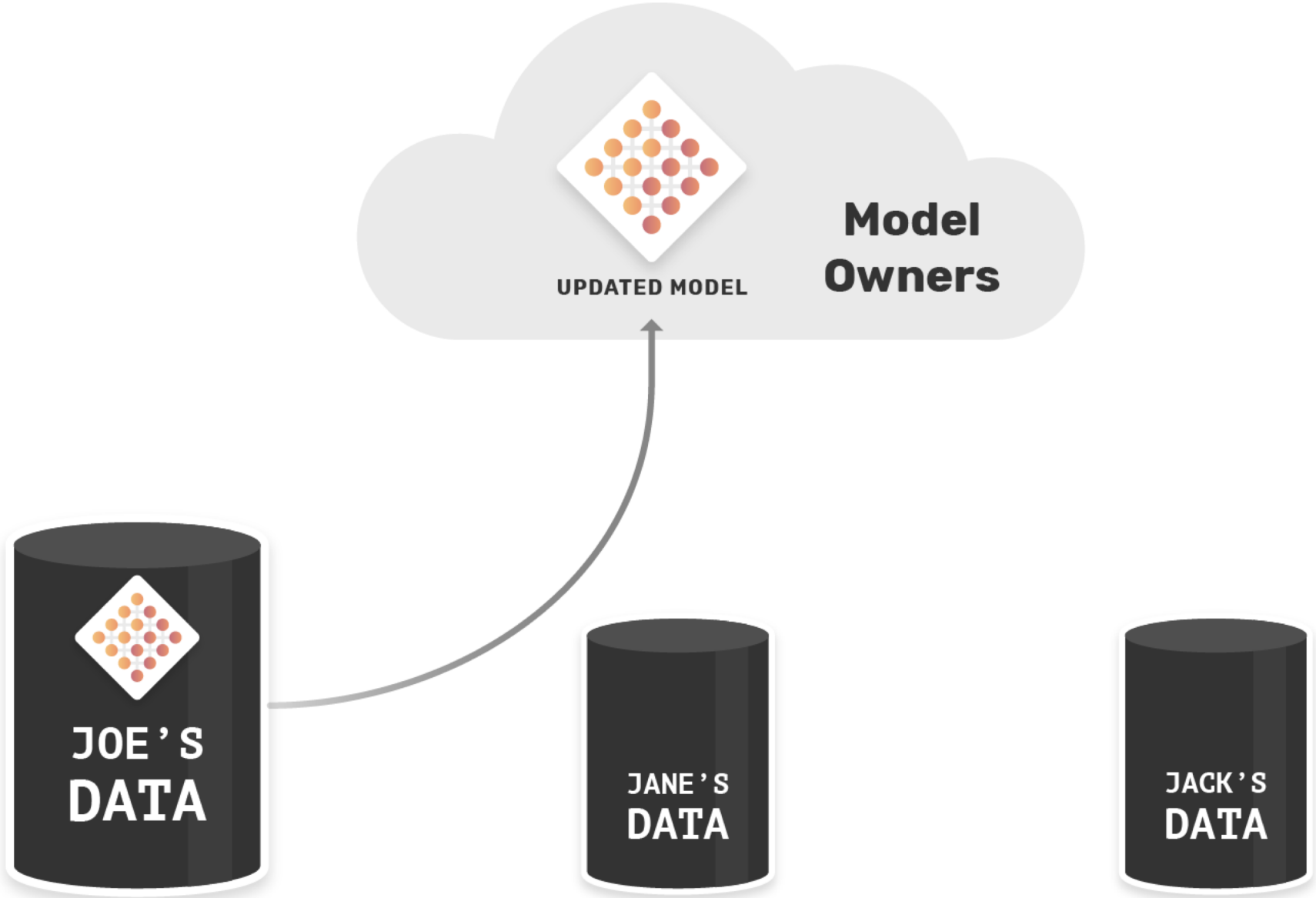
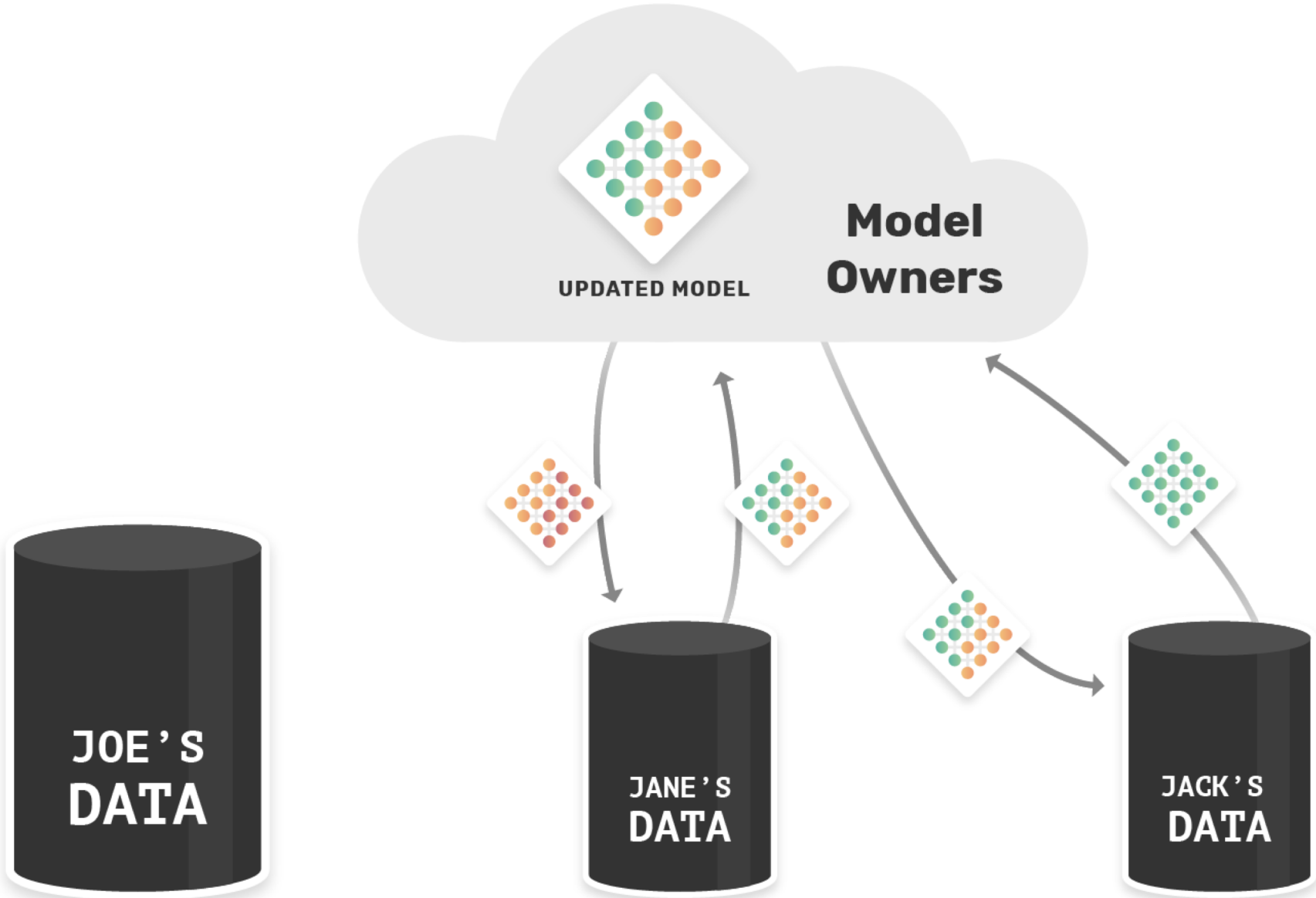
# Federated Learning

## Send the model, not the data.


INITIAL MODEL
Model Owners
JOE'S DATA
JANE'S DATA
JACK'S DATA


UPDATED MODEL
Model Owners
JOE'S DATA
JANE'S DATA
JACK'S DATA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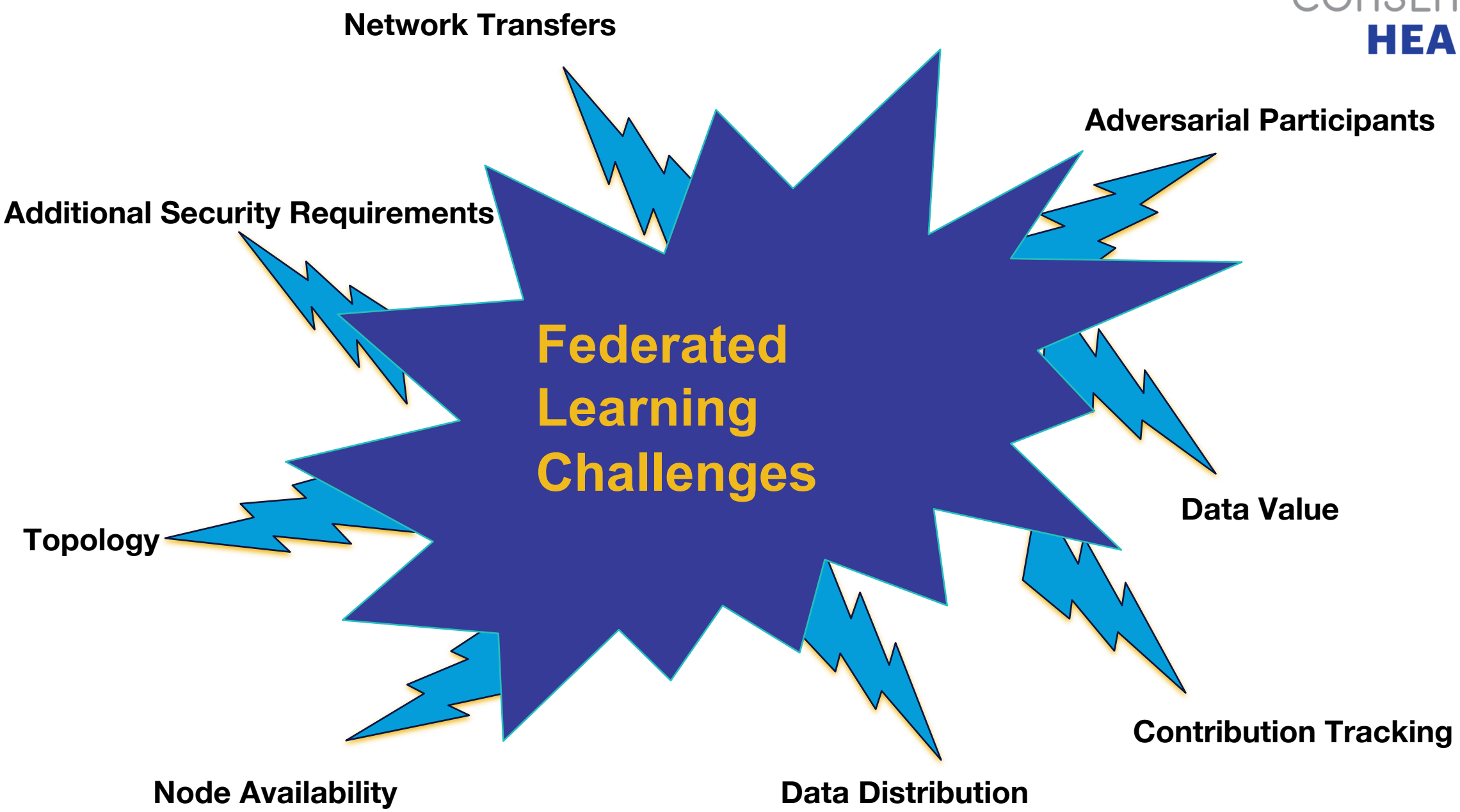

# Federated Learning

- Academic references
  - **Bonawitz et al.,** *Practical Secure Aggregation for Privacy-Preserving Machine Learning*, 2017
  - **Ryffel et al.,** *A generic framework for privacy preserving deep learning*, 2018
  - **Kairouz et al.,** *Advances and Open Problems in Federated Learning*, 2019
- Software implementations
  - PySyft https://github.com/OpenMined/PySyft/
  - TF Federated https://github.com/tensorflow/federated

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# Distributed Systems / Blockchains Enable:

**AUDITABILITY**

Add trust and traceability to the learning process / data access

+

**ETHICS / GOVERNANCE**

Combined with PETs - provide a transparent, tamper-proof way to implement policies on AI models

+

**MONETISATION**

From data sharing to data lending.

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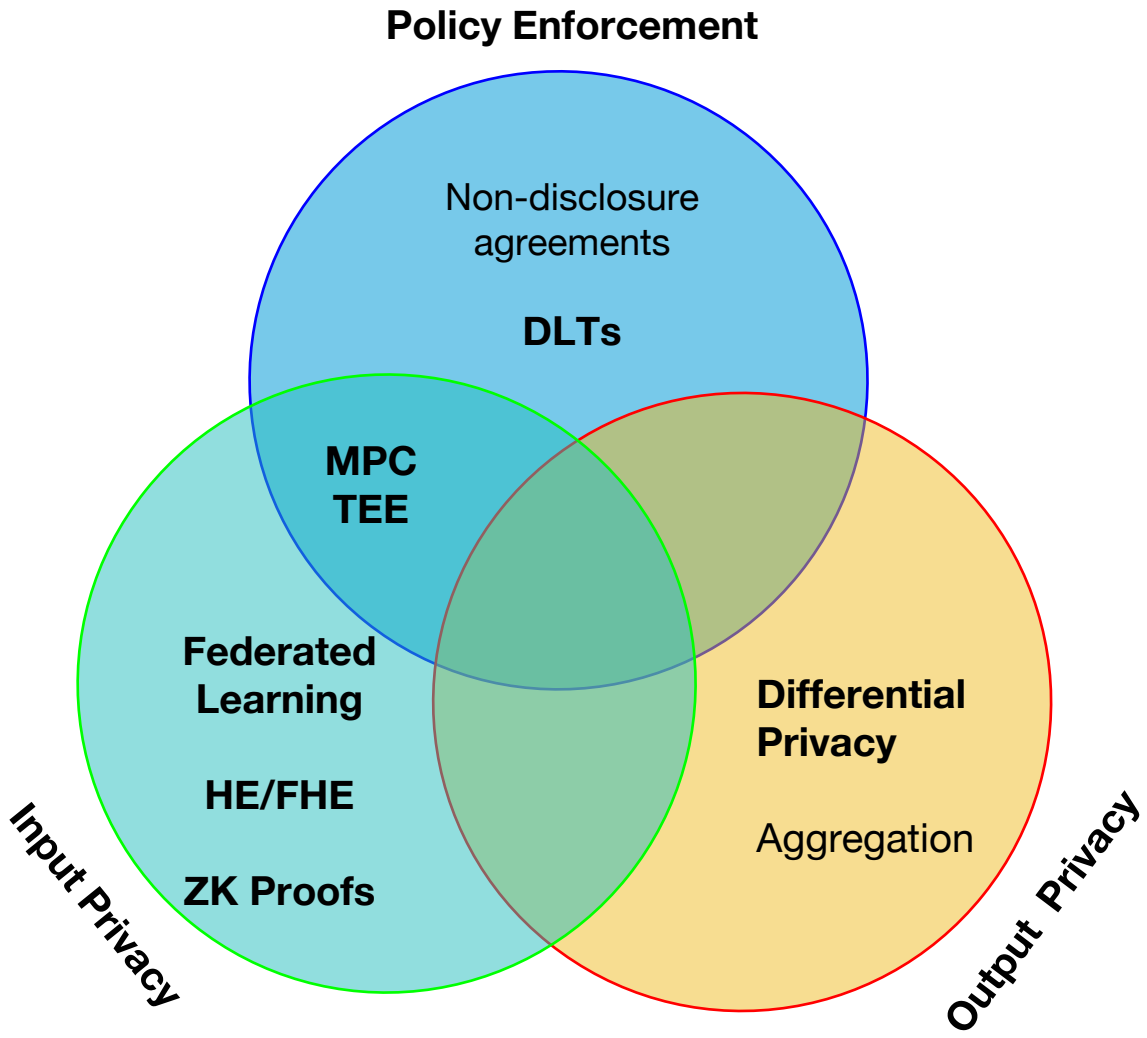
# Privacy Enhancing Technologies - **3 Categories**




*[Credits] UN Handbook on Privacy-Preserving Computation Techniques*

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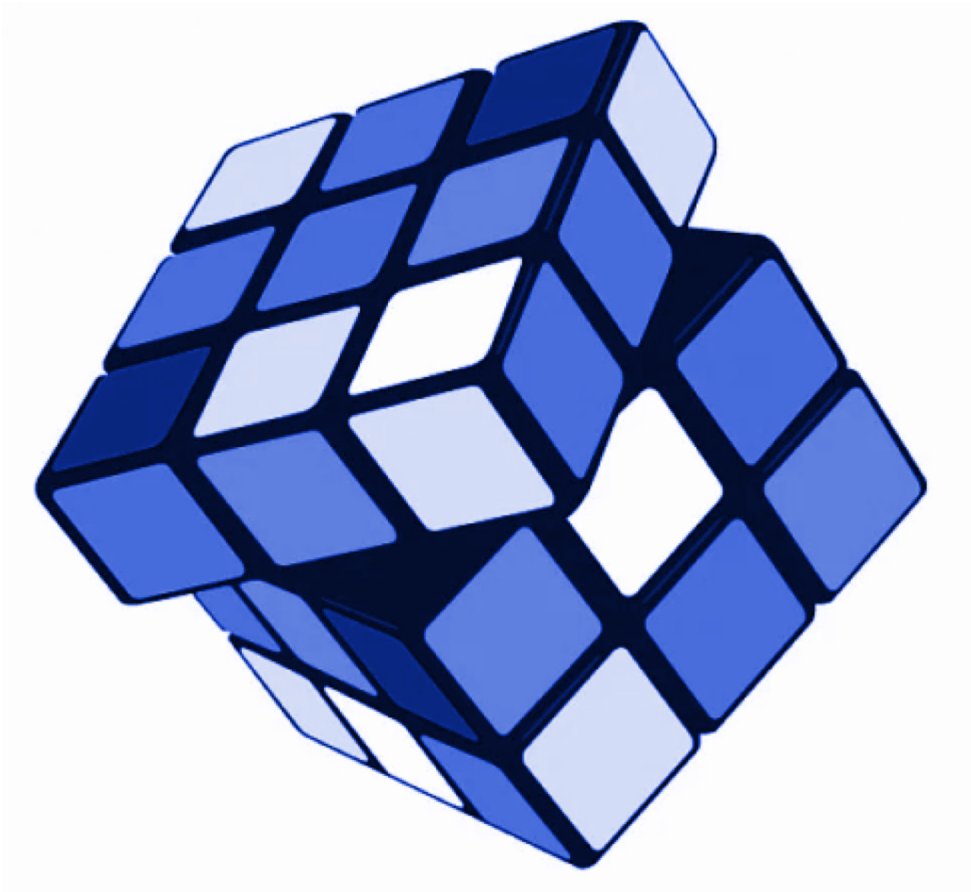
# Encrypted Computation - Challenges

- Computational requirements
- Numeric stability and precision
- Trusted third parties / hardware vendors
- TRAINING
- Adversaries and dishonest participants
- Leverage GPUs



# Secure Computing and Blockchain?

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**Elon Musk** @elonmusk · 12h

What should be developed on Ethereum?

960 764 4.3K

**Vitalik Non-giver of Ether**

@VitalikButerin

Follow

Replying to @elonmusk

## My top picks (1):

**Vitalik Non-giver of Ether** @VitalikButerin · 11h

(3)

* Markets for personal data for privacy preserving machine learning (you pay me X, I let you homomorphically execute function Y on my data that's been attestated to by Z...)

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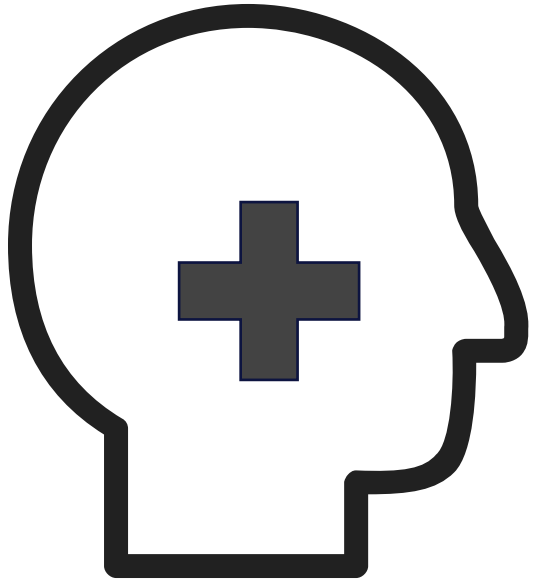
# Incentives Introduced



**ENCOURAGE**

**Good quality data**

**Honest computation**

**e.g. model update or inference**

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# Solve this by answering some questions:

If data is private, then how do we determine its quality?

- **Trusted Execution Environments?**
- **Model Improvement with respect to a test set?**

How do we avoid biasing models?

- **Avoid accepting only consistent data.**
- **SOMETIMES OUTLIERS ARE GOOD.**

# Conclusion - Critical Elements

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| | |
|---|---|
| A | Data and analytic processes discoverable on a secure public blockchain while retaining privacy of the data and analytic processes |
| B | Value fabricated by generating data/compute matches that were previously illegal, unethical, and infeasible |
| C | Compute guarantees provided by federated learning and advanced cryptography |
| D | Privacy guarantees provided by software (e.g., Homomorphic Encryption, Secure Multi-Party Computation, ...) and hardware cryptography (e.g., Intel SGX and AMD SEV-SNP) |
| E | Data quality incentivized via tokenized reputation-based rewards |
| F | Discarding of poor data accomplished via model poisoning attack prevention techniques |

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# Discussion

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# Thank you!

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# Thank you!