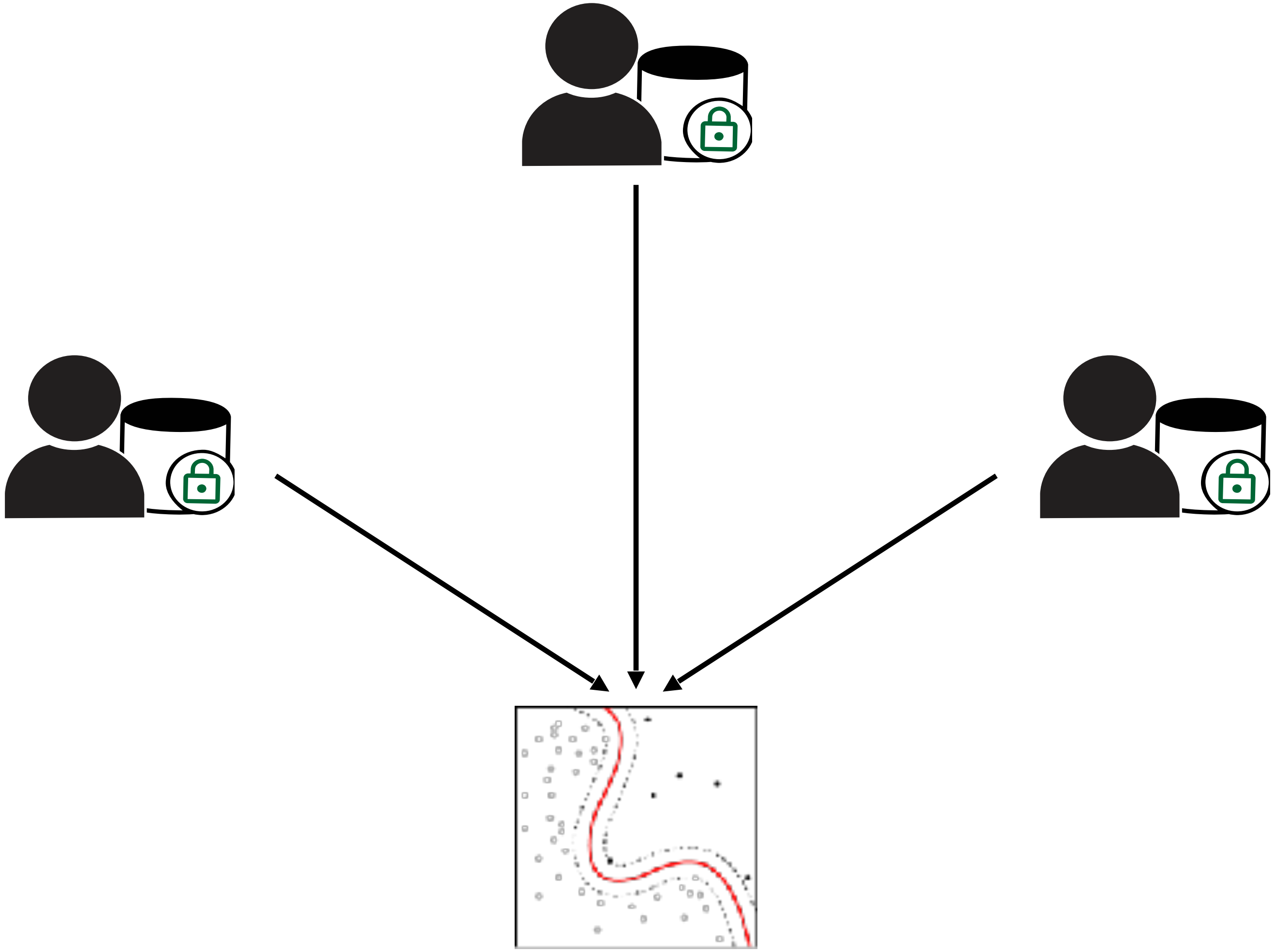
Fast & Faster Privacy-Preserving ML in Secure Hardware Enclaves

Nick Hynes, Raymond Cheng, Dawn Song | UC Berkeley & Oasis Labs
with support from the TVM team and community!

Ideal: data providers pool data to train a large, complex model



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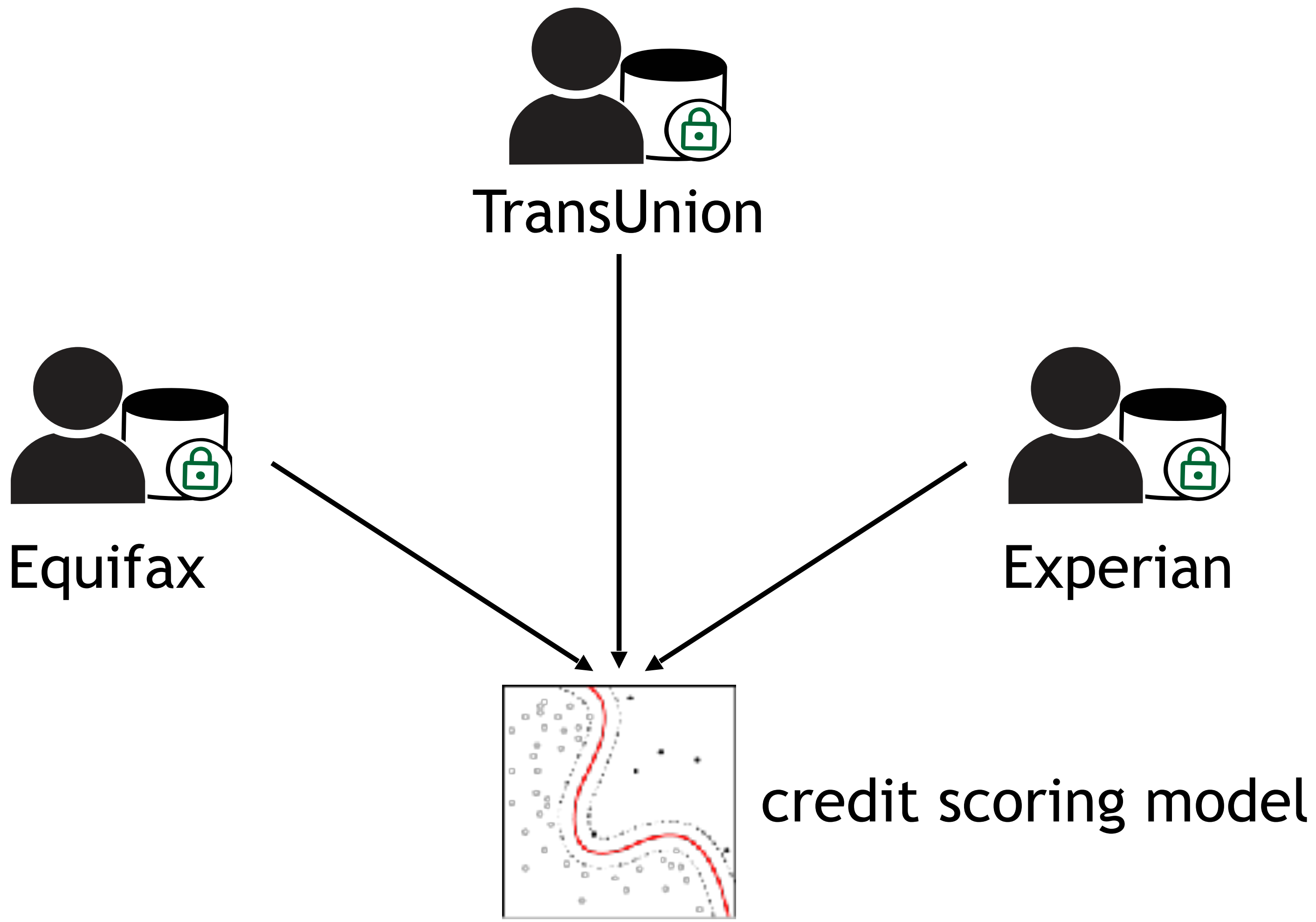

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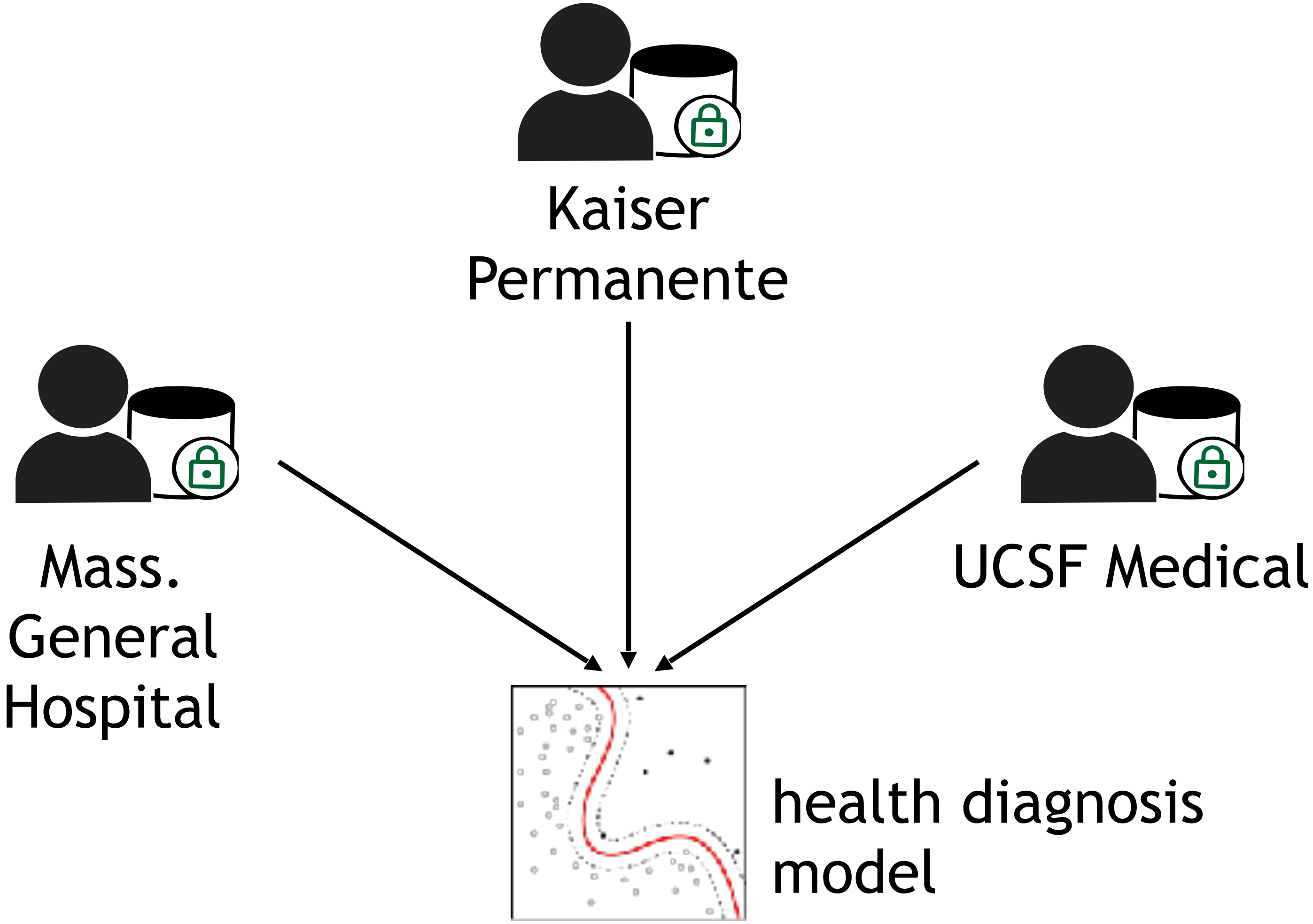

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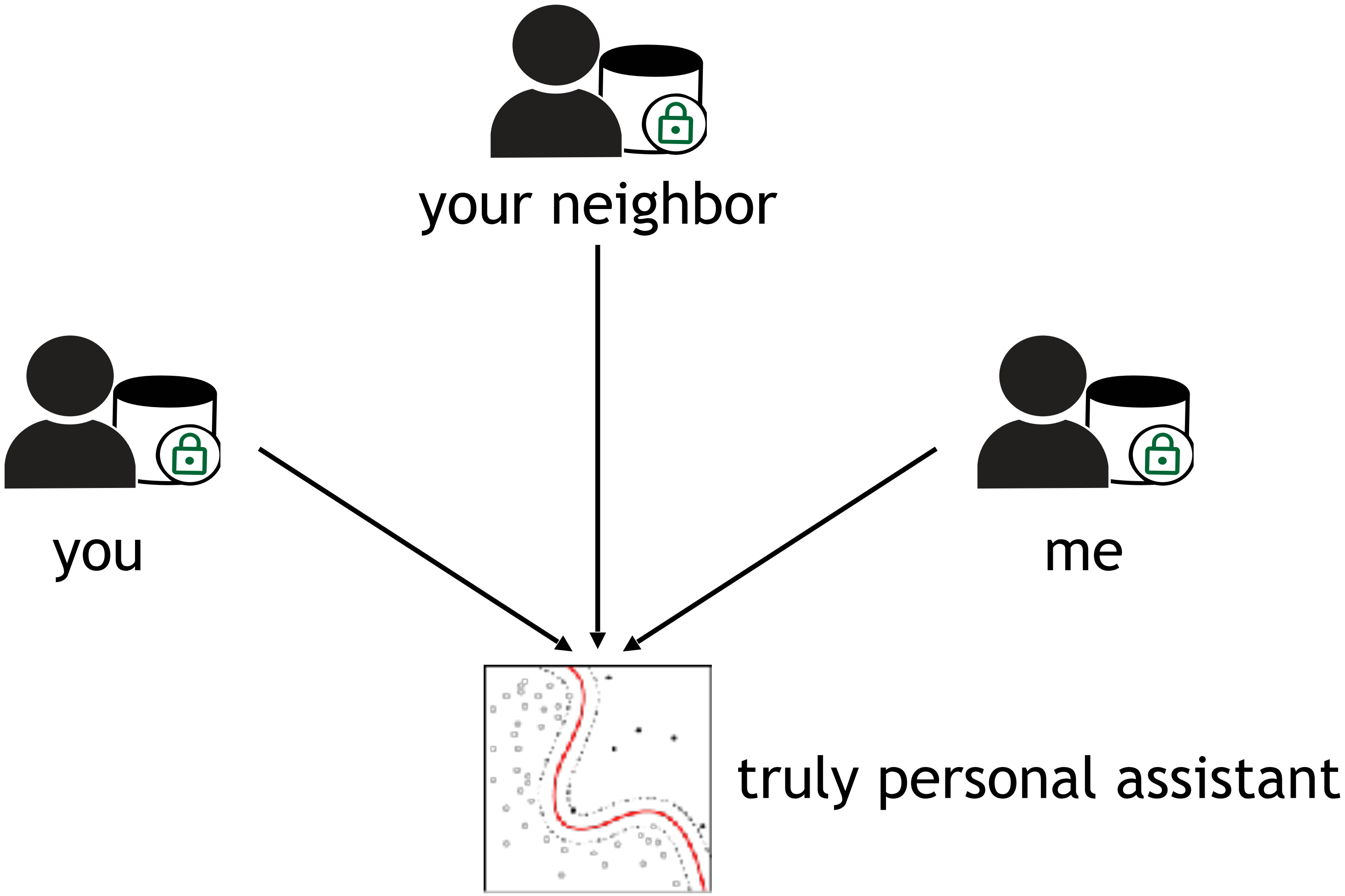
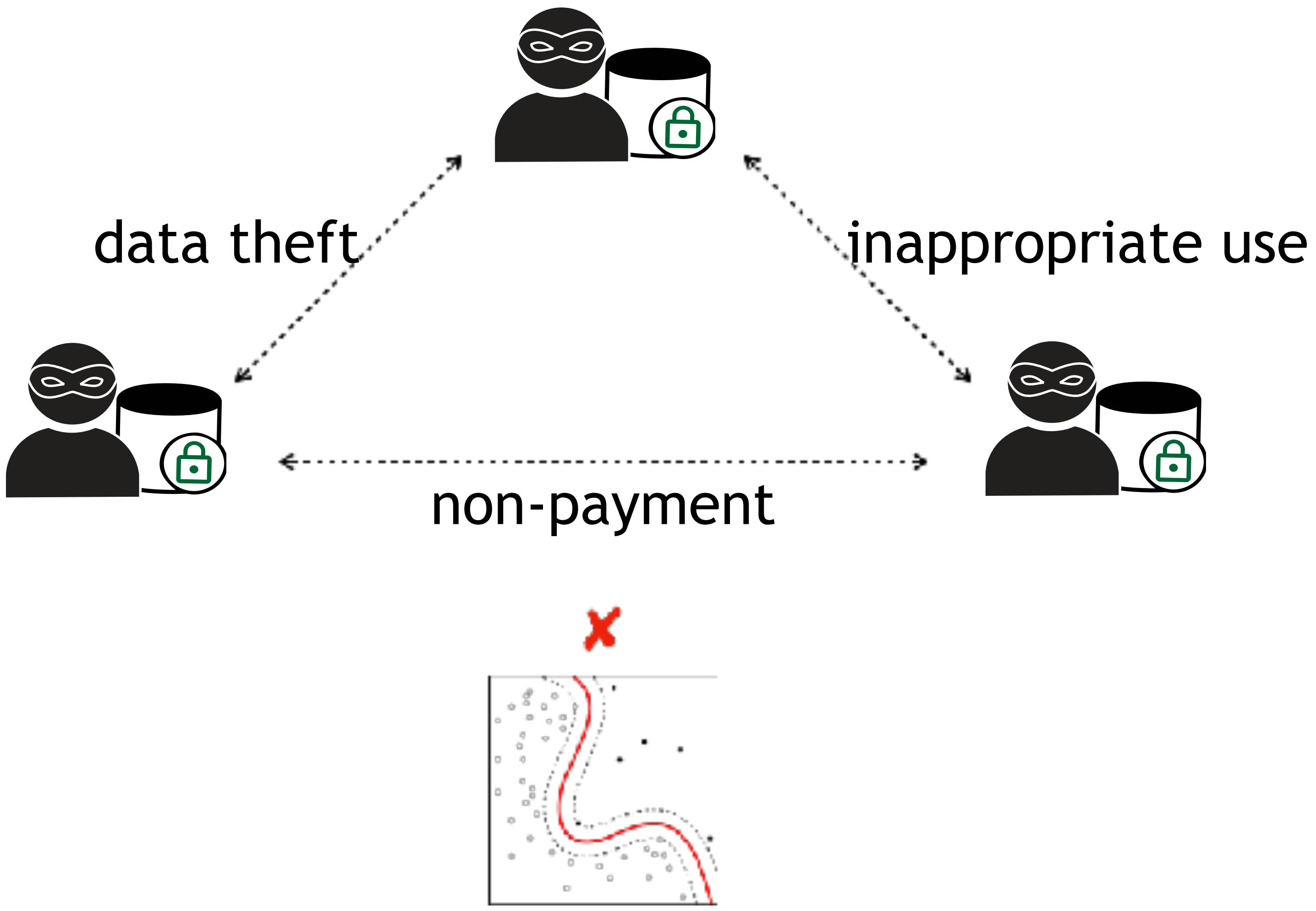
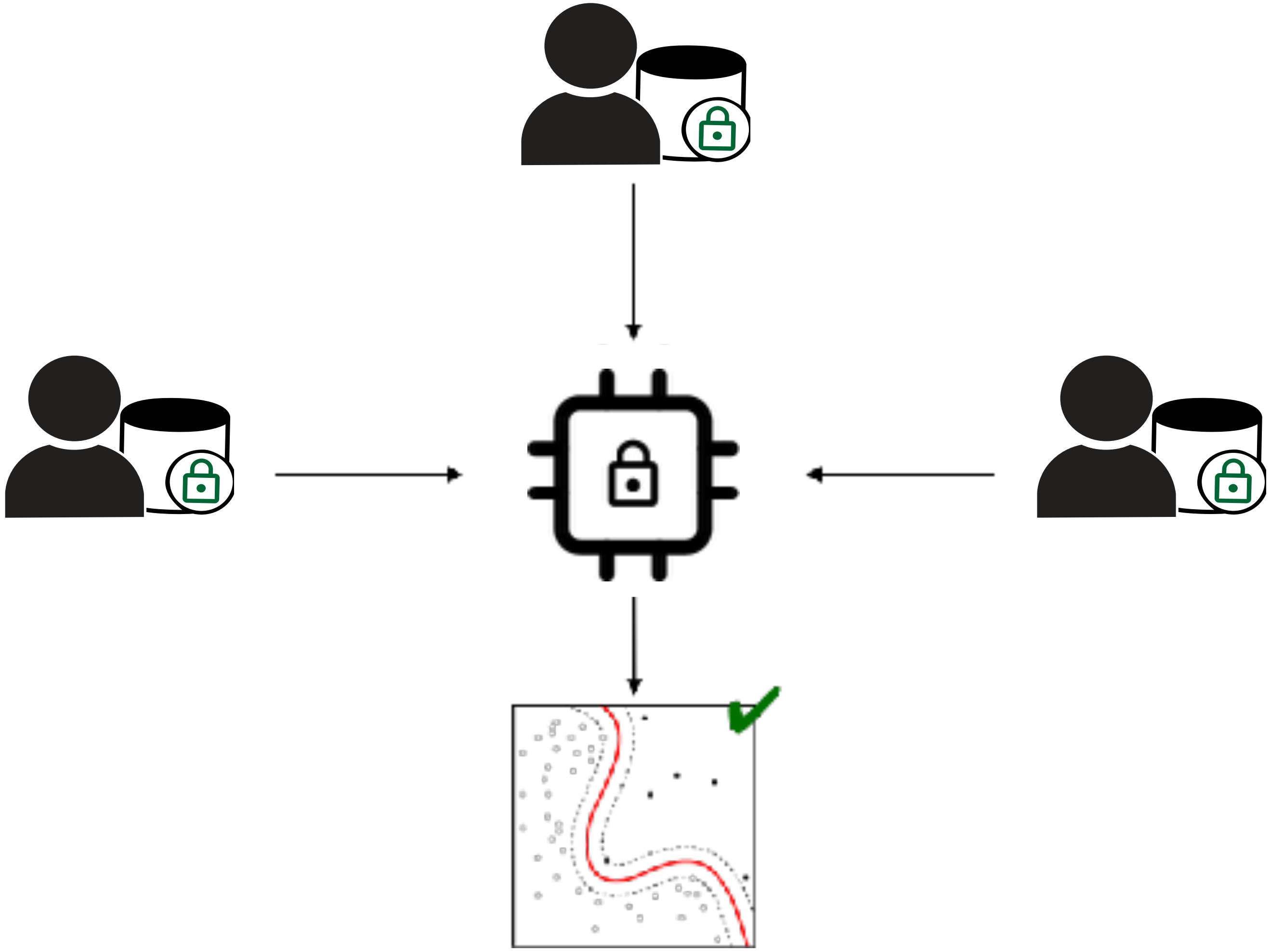


Reality: data providers are mutually distrusting!



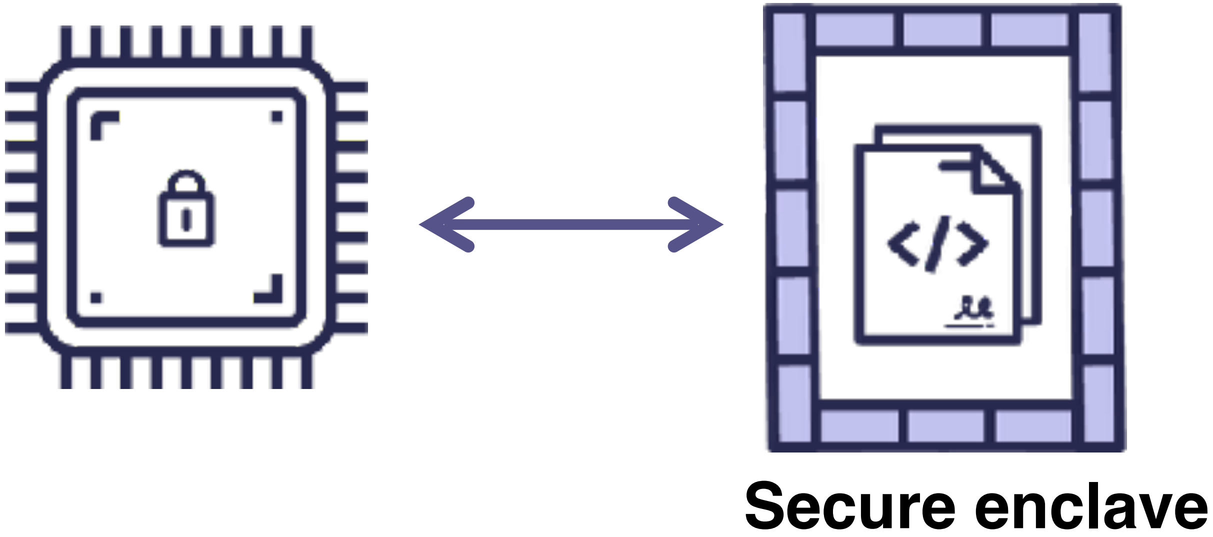
Solution: providers cooperate via a virtual trusted third party



Secure Computation Techniques

	Performance	Support for practical ML models	Security mechanisms
Trusted Execution Env. (TEE)	●●●	●●●	Secure hardware
Secure multi-party computation	●○○	●○○	Cryptography, distributed trust
Zero-knowledge proof	●○○	●○○	Cryptography, local computation
Fully homomorphic encryption	○○○	●○○	Cryptography

Secure Enclaves



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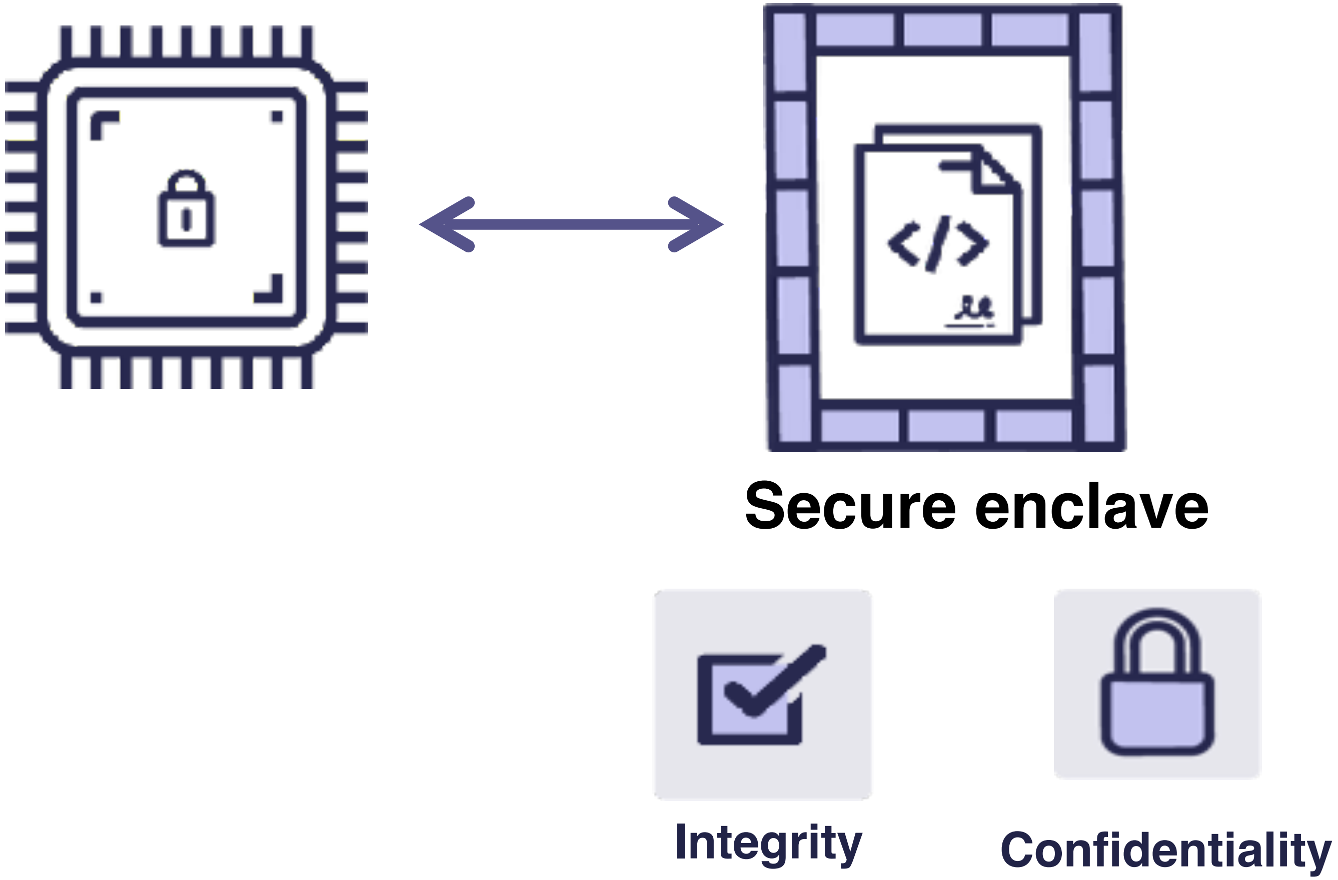

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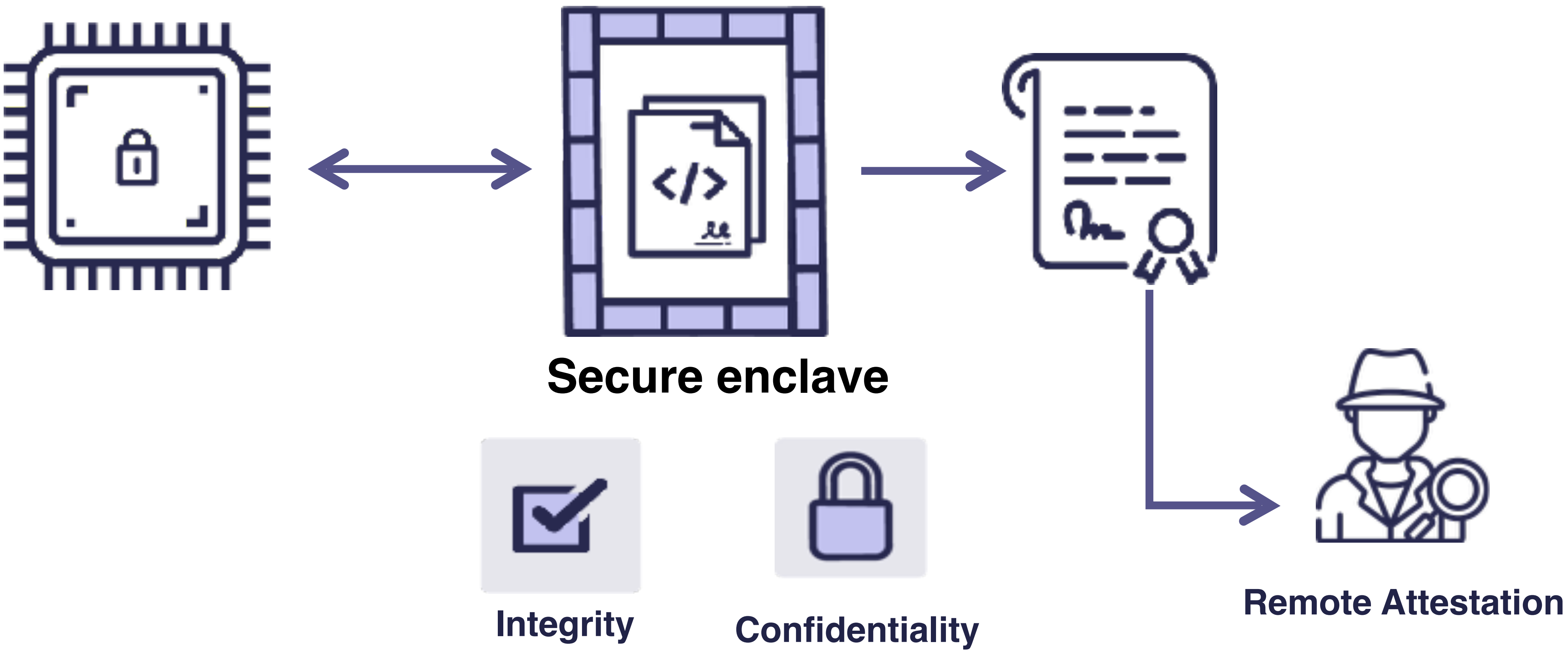

TEE Implementations

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- Keystone: the first open-source end-to-end secure enclave
    - runs on RISCV chips and FPGAs
    - keystone-enclave/keystone
- Ginseng: a drop-in enclave framework for FPGA ML accelerators

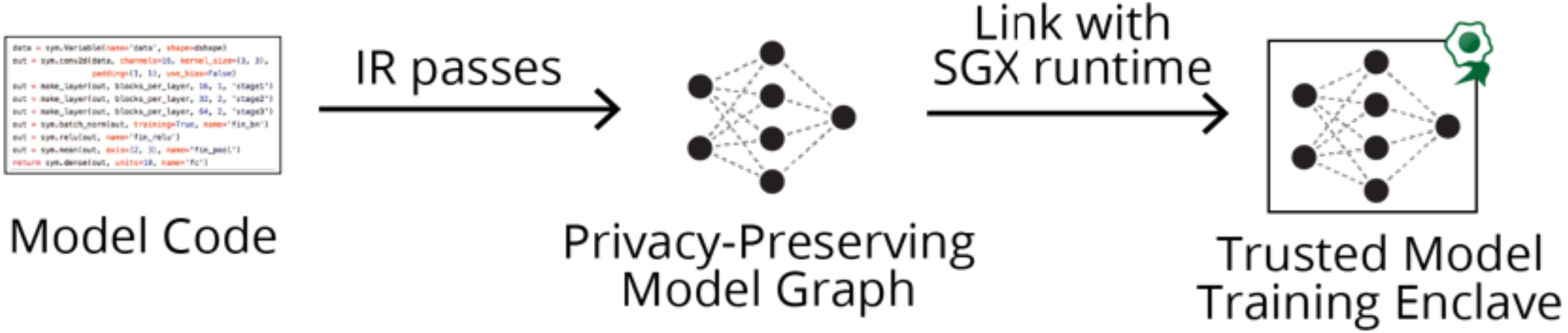
1. Privacy-Preserving ML & Secure Enclaves

2. Myelin: Efficient Private ML in CPU Enclaves

3. Ginseng: Accelerated Private ML in FPGA Enclaves

4. Sterling: A Privacy-Preserving Data Marketplace

Myelin: Efficient Private ML in CPU Enclaves



dmlc/tvm/apps/sgx
dmlc/tvm/rust

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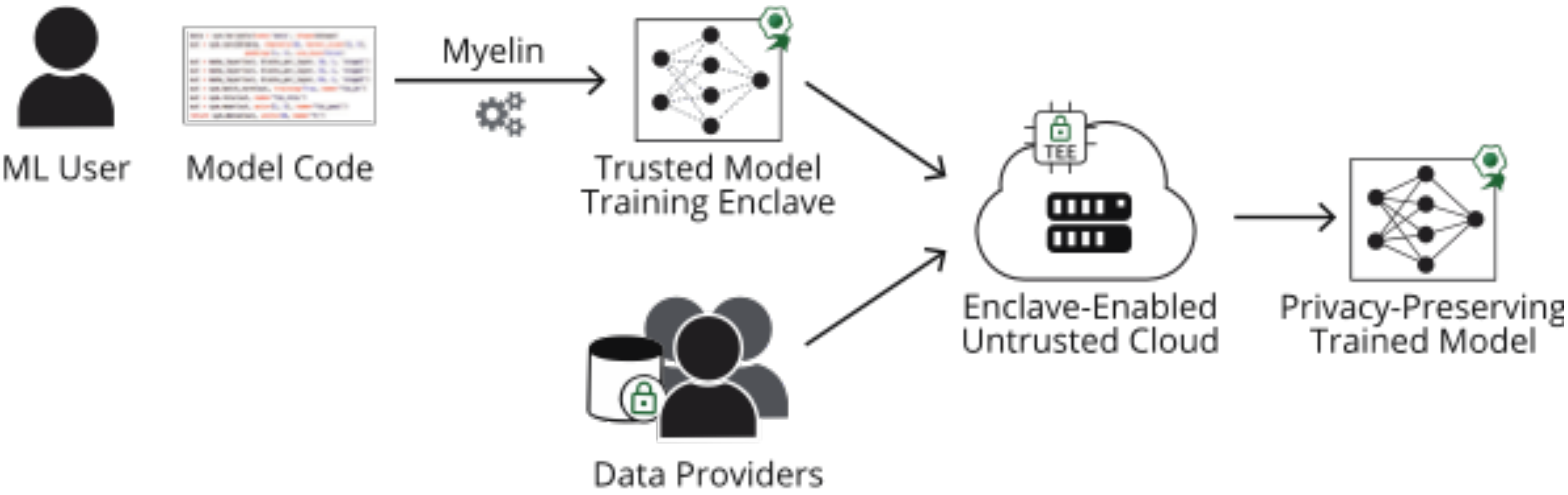

[3] Efficient Per-Example Gradient Computations. Goodfellow. 2015

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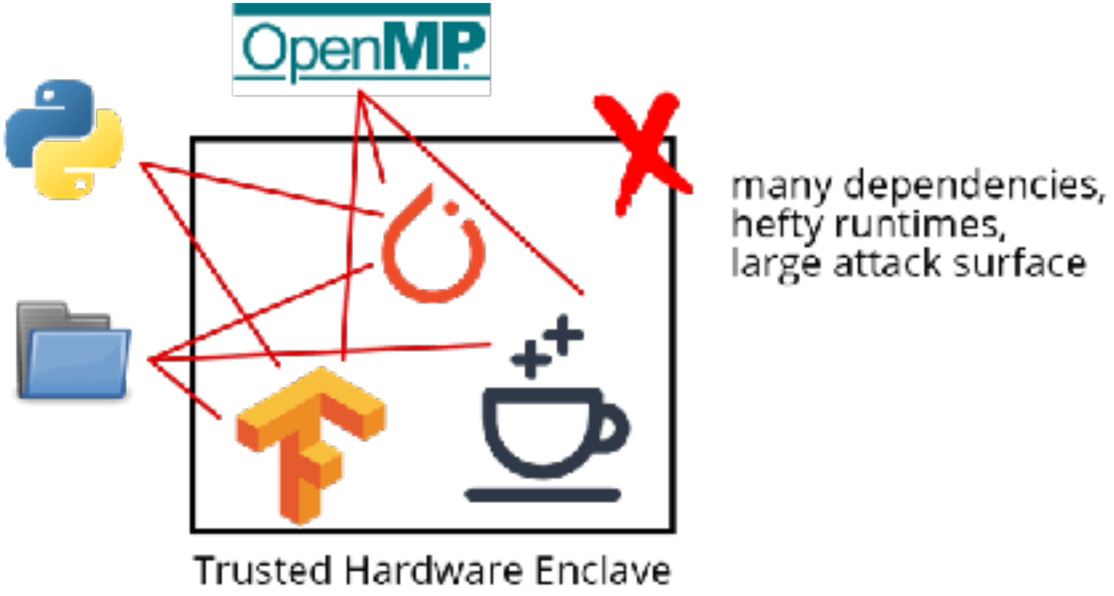

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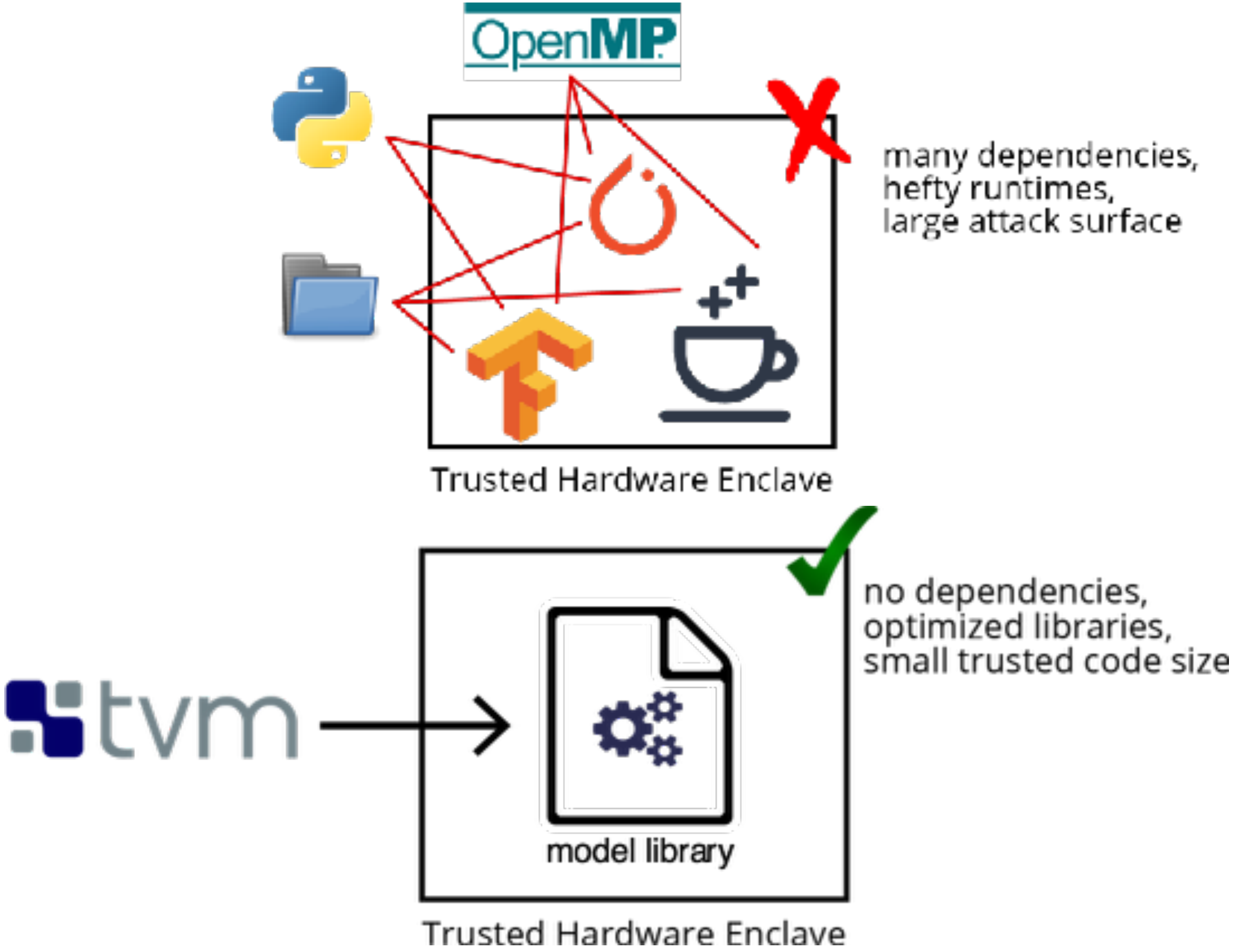

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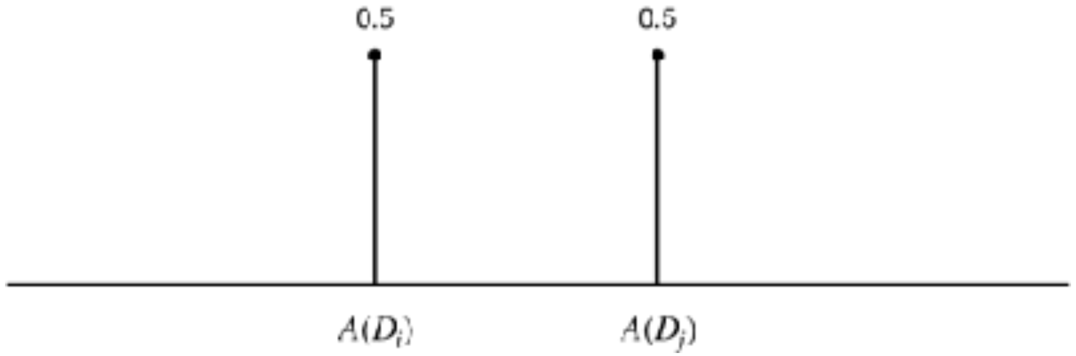

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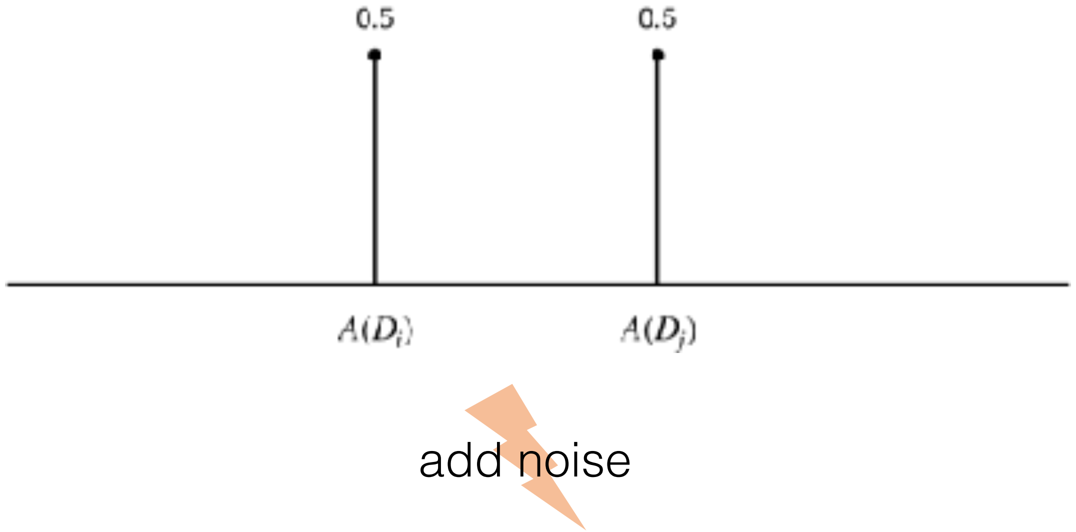

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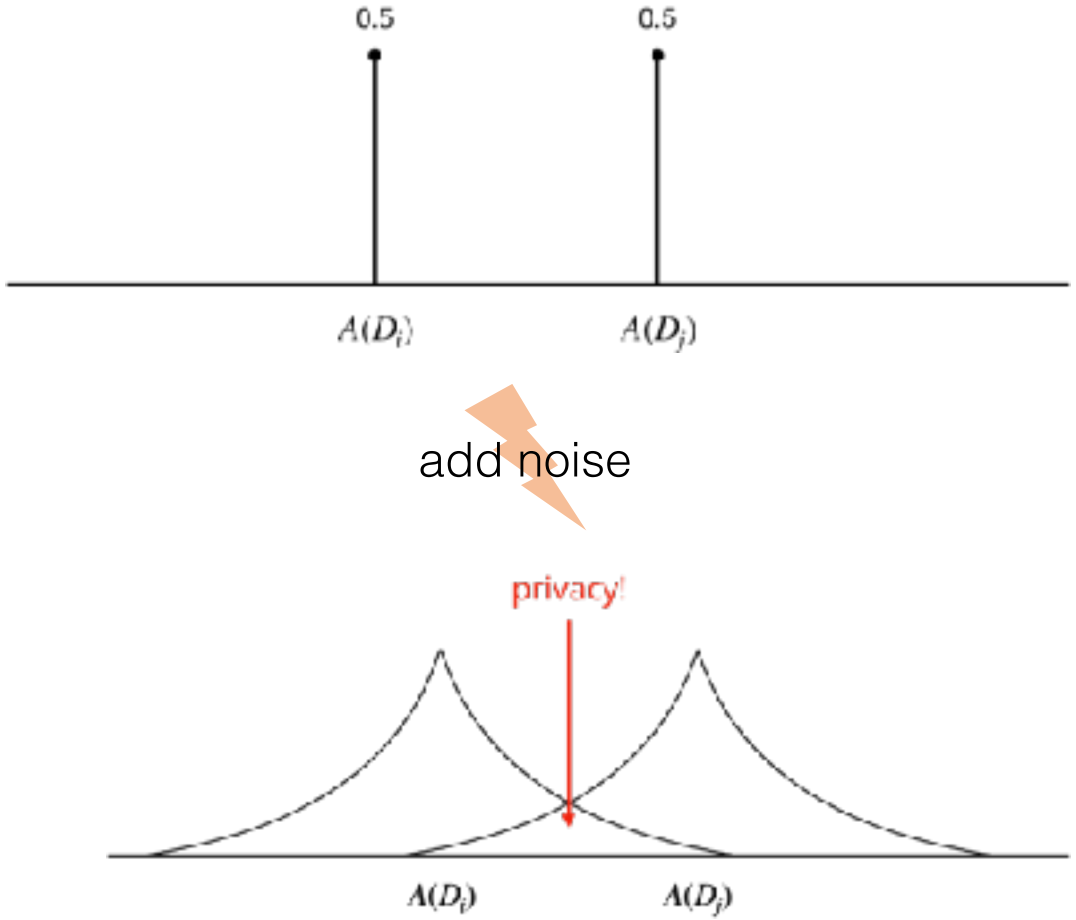

Step 3: Make it Fast

Differentially Private SGD

1. compute forward pass for mini-batch of *m* examples
2. compute *per-example gradients*
3. rescale each example's gradient to have unit norm
4. average them up
5. add noise
6. take gradient step

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add a pass to fuse these

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Differentially Private SGD

1. compute forward pass for batch of *m* examples
2. compute *per-example gradients*
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4. average + noise+ gradient step

autograd takes O(m) [4]
O(1) with custom IR ops

[4] Efficient Per-Example Gradient Computations. Goodfellow. 2015

Step 4: Benchmark

Performance on CIFAR-10

	1 Myelin Enclave	non-private CPU	related work
VGG-9 (training)	21.3 img/s	27.2 img/s	Chiron (4 enclaves) [5] 24.7 img/s
ResNet-32 (training)	12.4 img/s	13.6 img/s	-
MobileNet (inference)	32.4 img/s	-	Slalom (enclave+GPU) [6] 35.7 img/s

[5] Chiron: Privacy-preserving machine learning as a service. Hunt, Song, Shokri, Shmatikov, and Witchel. 2018
[6] Slalom: Fast, Verifiable and Private Execution of Neural Networks in Trusted Hardware. Tramer and

State of the Art Performance for ML in Single CPU Enclave

- but a CPU is a CPU: ½ day to train a ResNet is emotionally unsatisfying
- no GPU TEEs (yet), but we *can* do FPGAs!

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Ginseng, the Learning TEE

- Main idea: FPGA can be programmed with ML accelerator (VTA) *and* the components required to make a TEE
  - memory encryption
  - key generation
  - remote attestation

- TEEs are general-purpose; ML is very particular
  We get big efficiency wins from specializing TEE to ML workloads

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- End result: an end-to-end secure, speedy ML pipeline

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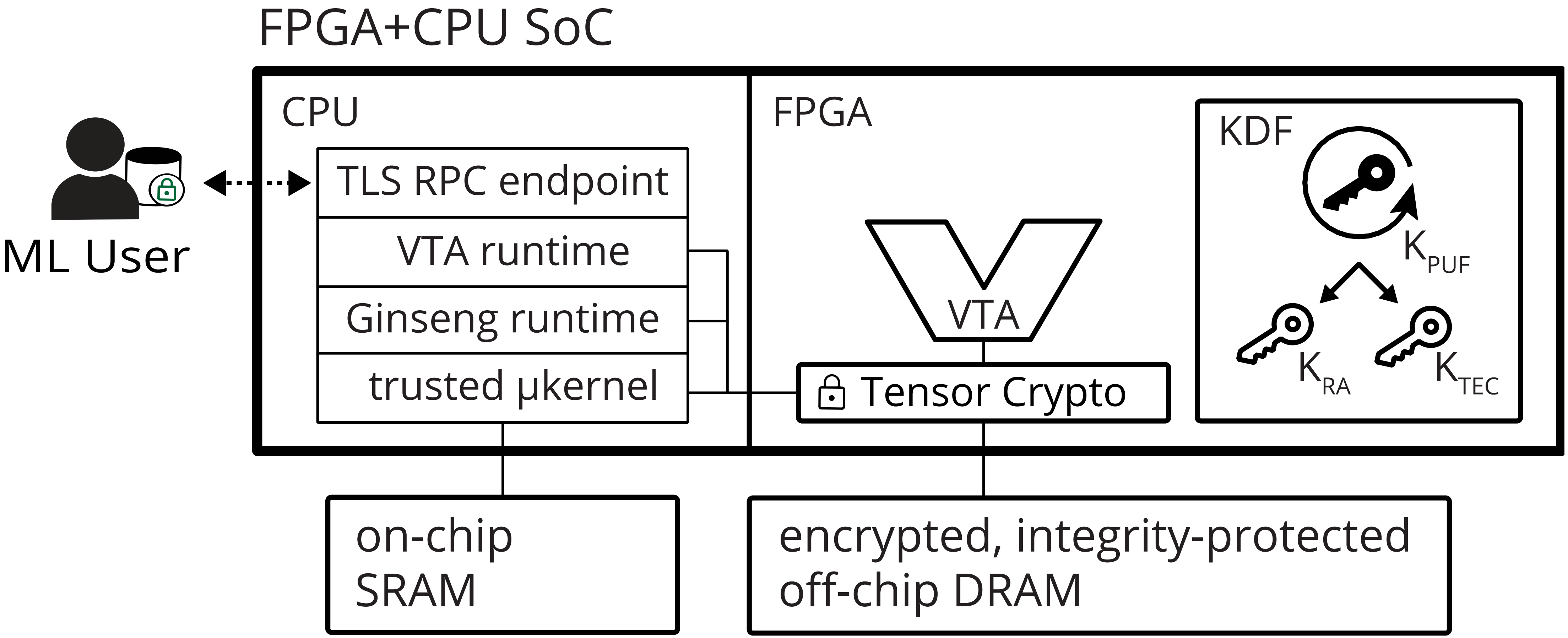

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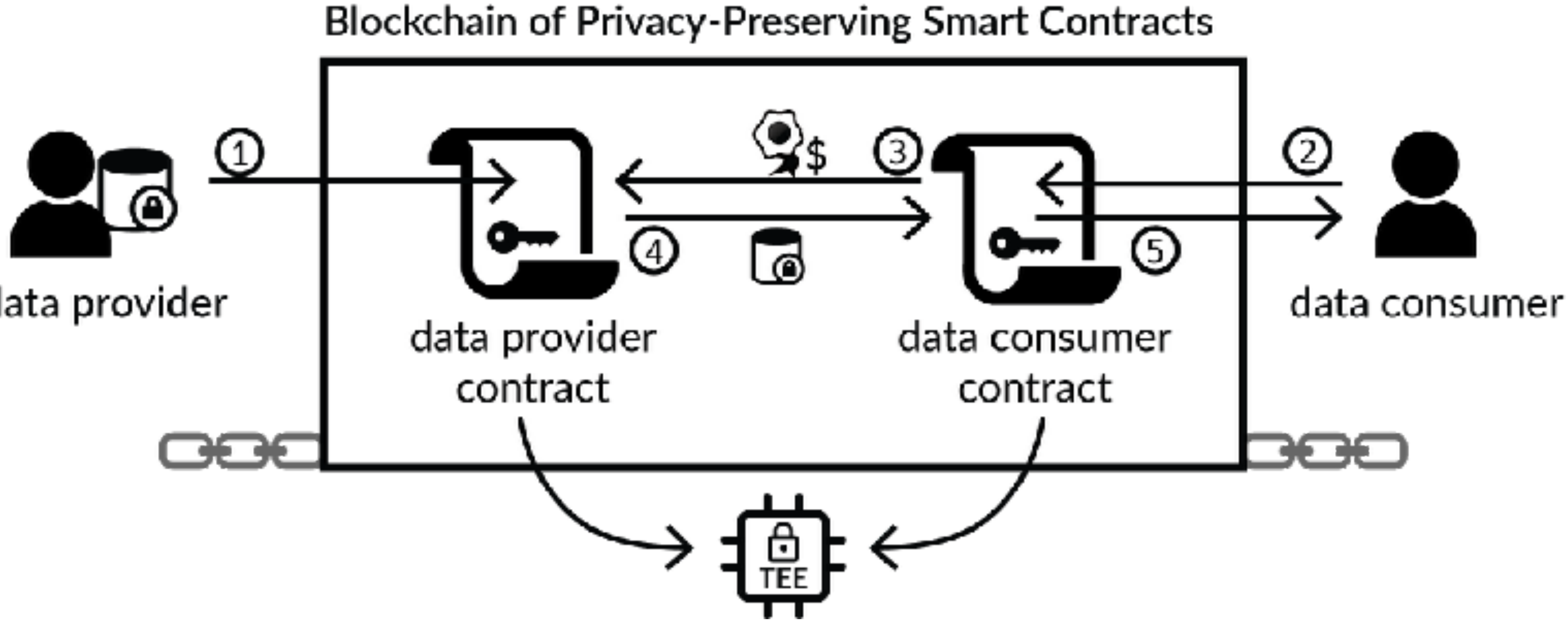
Sterling: A Privacy-Preserving Data Marketplace built on the Oasis blockchain and TVM



[1] A Demonstration of Sterling: A Privacy-Preserving Data Marketplace. VLDB 2018.
[2] Ekiden: A Platform for Confidentiality-Preserving, Trustworthy, and Performant Smart Contract Execution. 2018.

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   and sends back data
5. consumer contract trains a privacy-preserving model and returns it to
   the data consumer

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- TVM modules run in secure enclaves provided by the Oasis blockchain

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- Deploy Ginseng to AWS F1 once VTA Chisel port is ready
- automatically checking TVM models for differential privacy
  (on the blockchain, of course)

Thanks!