Jolt-FL: A General-Purpose Verifiable Federated Learning Framework Powered by zkVM

From Jolt zkVM to the Future of zkML

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- **Track:** CISS-11 – Communication and Information System Security
- **Talk:** Verifiable Federated Learning over zkVM

Outline

- Motivation: **why verifiable federated learning?**
- From zk-SNARKs to zkVMs and zkML
- Jolt zkVM
- Jolt-FL design: proving each local training step
- Evaluation on MNIST and robustness to malicious clients
- Jolt vs. Jolt-FL and the road ahead for zkML

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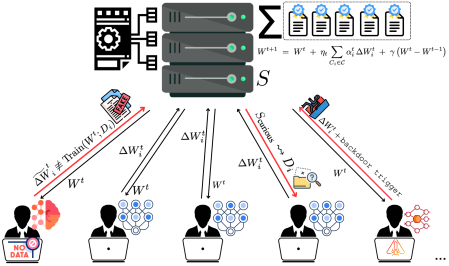
Why Verifiable Federated Learning?

- **Federated Learning (FL):** clients collaboratively train a model without sharing raw data.
- In practice, many clients are **untrusted**: phones, IoT devices, vehicles, or edge servers.



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  - Random or adversarial gradients (Byzantine / poisoning attacks).
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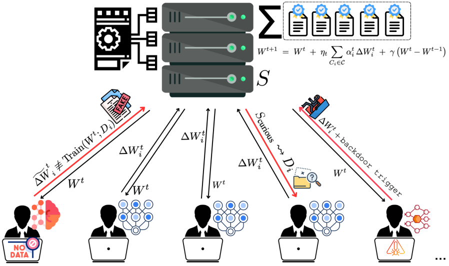

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Why Verifiable Federated Learning? (cont.)

- Existing defenses: robust aggregation, anomaly detection, heuristics.
- **Goal:** cryptographically guarantee that each accepted update really came from running the prescribed training algorithm on some data.

FL update rule

$$W_{t+1} = W_t + \frac{1}{|C_t|} \sum_{i \in C_t} \Delta W_i$$

$$\Delta W_i = \mathrm{Train}(W_t, D_i)$$

From zk-SNARKs to zkVMs and zkML

- Early zkML: hand-written circuits for specific models or layers
  - E.g., zkCNN, specialized SNARKs for inference on small networks.
- Limitations:
  - Hard to maintain as models and training code change.
  - Each new architecture requires new circuit engineering.
- **zkVM approach** (a16z, others):
  - Treat the prover as emulating a CPU (e.g., RISC-V) inside a SNARK.
  - Same VM can run arbitrary Rust / C / ML code, no new circuits.
- Vision for **zkML**:
  - Generic, developer-friendly ZK infrastructure for training and inference.
  - Think of zkVMs as a "ZK coprocessor" similar to GPUs for linear algebra.

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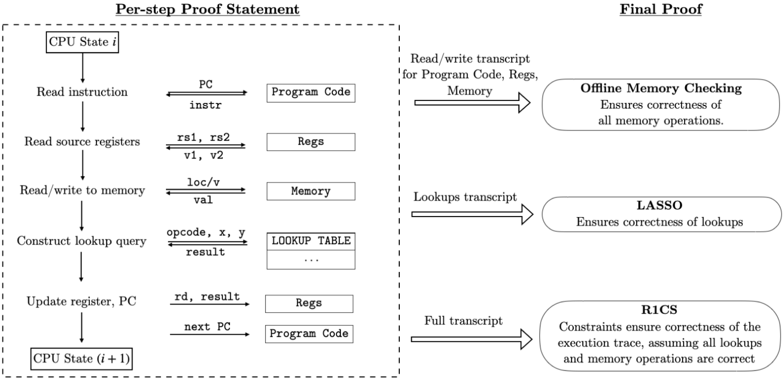
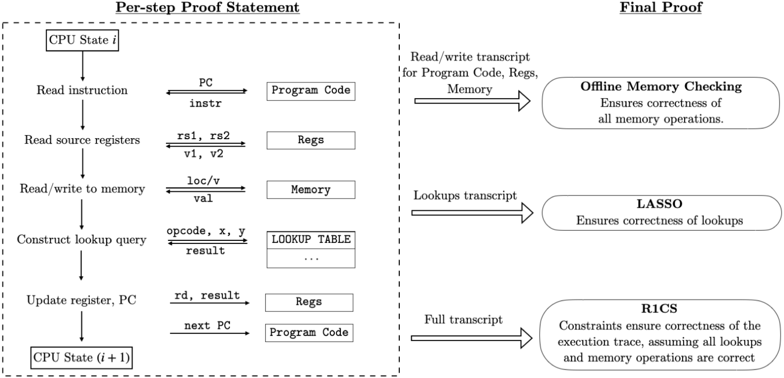
Jolt zkVM (1/3)



Source: Arun et al., “Jolt: SNARKs for Virtual Machines via Lookups”, 2024.

- Jolt is a **high-performance zkVM** from a16z crypto.
- Targets a **RISC-V** ISA; each instruction is enforced via a lookup into a large instruction table.

Jolt zkVM (2/3)



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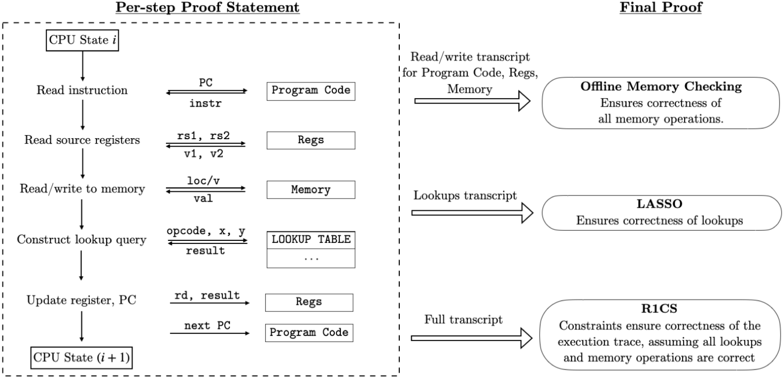
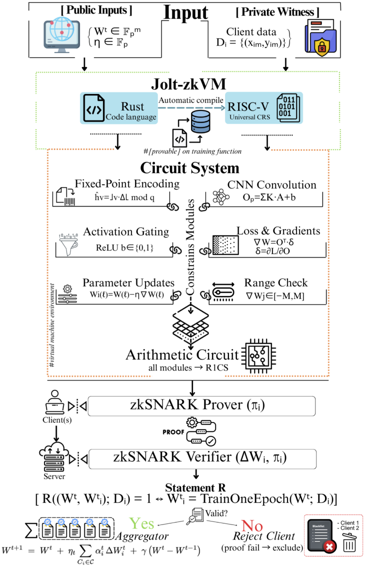
- **Key ingredients:**
  - Lasso-style **lookup argument** for instruction semantics.
  - Spice-style **RAM consistency** checking.
  - **Polynomial commitments** (e.g., KZG) enabling recursion.

Jolt zkVM (3/3)



- **Benefits for ML:**
  - Fixed-point–friendly field for 32/64-bit arithmetic.
  - Uniform zkVM backend for training, preprocessing, and aggregation.
  - No model-specific circuits: we prove execution of normal ML code.

Jolt-FL: High-Level Idea



- **Each client:** run local training program inside Jolt zkVM.
- Output: model update ΔW_i and proof π_i of correct training.
- **Server:** verifies π_i and aggregates only valid ΔW_i.

What Does One Jolt-FL Proof Attest To?

- **Public statement:**
  - Initial model W_t and client output W_i^{t+1} (or update ΔW_i).
  - Round number, learning rate η, and other hyperparameters.
- **Witness (private):**
  - Client dataset D_i (MNIST images and labels in our prototype).
  - Full execution trace of the training program inside Jolt.
- **The proof π_i guarantees:**
  - Running the fixed training program P on (W_t, D_i) inside Jolt produces W_i^{t+1}.
  - All forward, backward, and update steps follow the specified equations.
  - Zero-knowledge: the verifier learns nothing about D_i beyond ΔW_i.

Informal NP statement:

$$R\big((W_t, W_i^{t+1}), (D_i, \tau_i)\big) = 1 \iff \tau_i : P(W_t, D_i) \to W_i^{t+1}.$$

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Encoding CNN Training in Jolt zkVM (1/3)

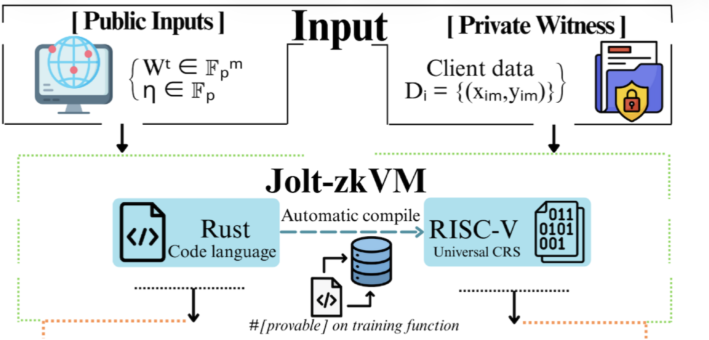
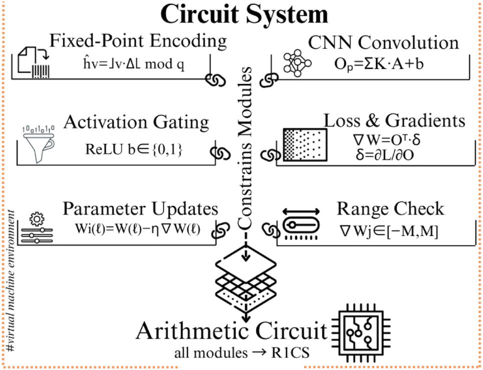


Figure: CNN code in Rust compiled to RISC-V and executed inside Jolt.

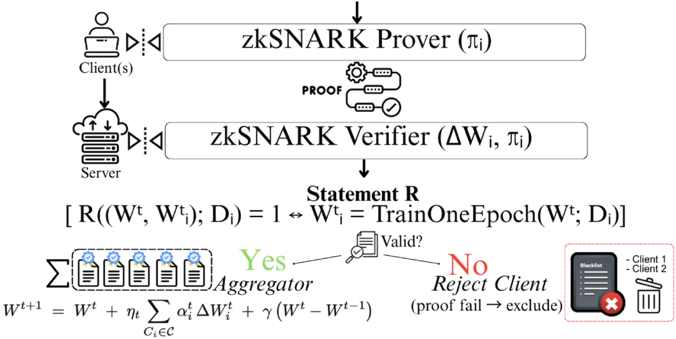
- We implement an end-to-end CNN in **Rust** and compile it to **RISC-V**.
- Jolt then arithmetizes the RISC-V execution into constraints inside the zkSNARK.

Encoding CNN Training - constrained inside the zkVM. (2/3)



- **Forward pass:** convolutions, ReLUs, pooling, fully connected layer.
- **Loss and gradient:** cross-entropy loss, backpropagation all layers.
- **Parameter update:** enforce $W_i^{t+1} = W_t - \eta \nabla_W \mathcal{L}(W_t; D_i)$.
- Constraints tightly link the gradient to the actual data batch D_i, so any deviation immediately breaks the proof.

Encoding CNN Training in Jolt zkVM (3/3)



- **Client side:** each client is a zkSNARK *prover* and sends its update (ΔW_i) together with a proof π_i.
- **Server side:** the server is the *verifier*; it checks each proof. Valid updates are marked **Yes**, invalid ones are **rejected**.
- **Aggregation:** the new global model is computed from *only* the verified updates; bad clients will be blacklisted.

Zero-Knowledge FL Round (Algorithm Sketch)

Jolt-FL round t

1. Server broadcasts (W_t, η_t) to participating clients.
2. Each client C_i:
   - 2.1 Runs one local epoch of training on D_i **inside Jolt.**
   - 2.2 Computes $\Delta W_i = W_i^{t+1} - W_t$.
   - 2.3 Generates proof π_i for (W_t, W_i^{t+1}).
   - 2.4 Sends $(\Delta W_i, \pi_i)$ to the server.
3. Server verifies each π_i and discards invalid updates.
4. Aggregates verified updates:

$$W_{t+1} = W_t + \frac{1}{|C_t|} \sum_{i \in C_t} \Delta W_i.$$

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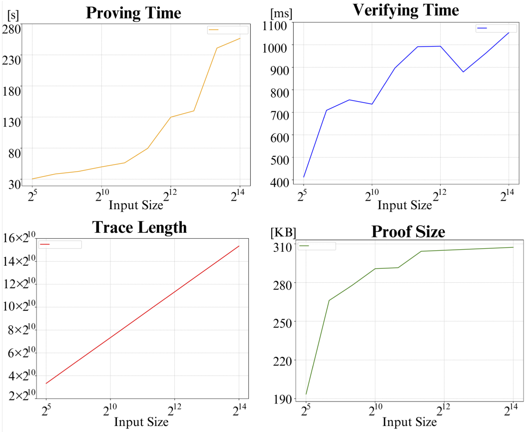
Evaluation Setup

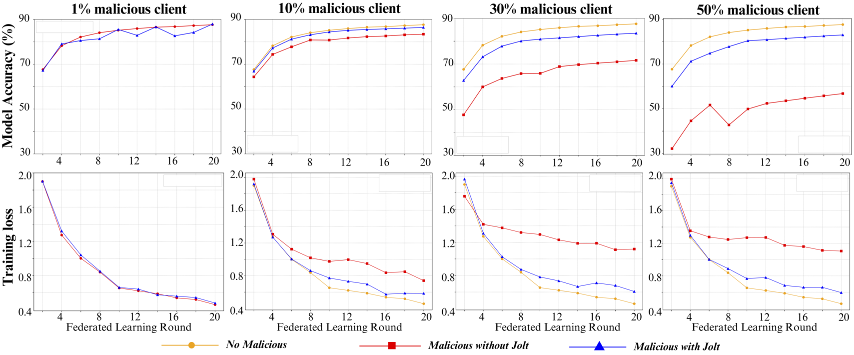
- Platform: Apple M3 MacBook Pro, 8-core CPU, 16 GB RAM.
- Dataset: **MNIST** handwritten digits.
- Model: lightweight CNN
  - Two 3×3 convolutional layers (4 filters), 2×2 max pooling, ReLU, fully connected output layer.
- FL configuration:
  - 10 clients, each with 6,000 local images.
  - 20 FL rounds; mini-batches of 50 images.
  - Learning rate $\eta = 0.02$.
- To reduce overhead we also explore **partial proofs** over selected batches/weights.

Performance Results: Proving / Verification / Size

- Proving per client: **tens of seconds** (~ 10–$15\times$ slower than native).
- Verification: $<$ **1 s** per proof.
- Proof size: **190–310 KB**, comparable to model update.
- **Proving is the main bottleneck.**
- **Verification and proof size are modest.**

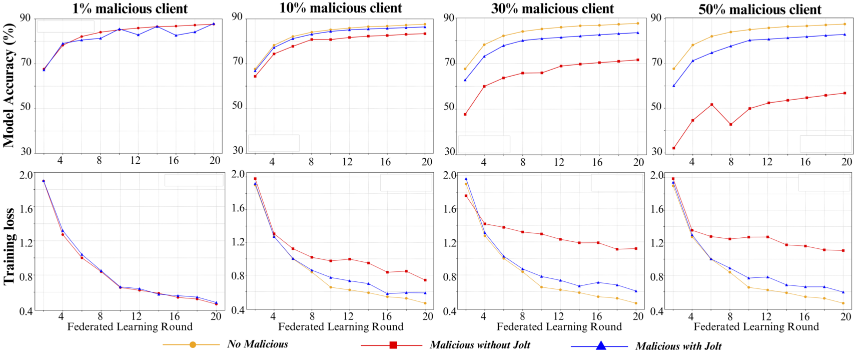


Accuracy and Robustness: Convergence (1/2)



- **Convergence:** Jolt-FL **matches** standard FL accuracy on MNIST.
- 20 rounds: similar test accuracy; fixed-point arithmetic does **not** hurt learning.

Accuracy and Robustness: Malicious Clients (2/2)



- **Scenario:** 10%, 30%, 50% clients send adversarial updates.
- Standard FL loses about **40–60%** accuracy.
- Jolt-FL **rejects** invalid updates, keeping roughly **80–90%** accuracy even at 50% malicious clients.

Jolt vs Jolt-FL & the zkML Roadmap

- **Jolt (a16z zkVM):**
  - General-purpose zkVM for RISC-V programs.
  - Designed for programmable ZK and efficient recursion/accumulation.
- **Jolt-FL (our work):**
  - First end-to-end verifiable FL framework built directly on a zkVM.
  - No custom circuits; we reuse the same VM for ML code and protocol logic.
  - Demonstrates feasibility of proving realistic CNN training inside FL.
- **Towards future zkML:**
  - Larger models and more complex workloads.
  - Partial proofs, better arithmetization, hardware acceleration.
  - Combining zkVMs with folding / accumulation schemes for scalability.

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Limitations and Future Work

- **Prover cost:** still too heavy for many real deployments.
- **Threat model:**
  - We guarantee *correct execution*, not *good data*.
  - Semantic poisoning or label manipulation are still possible.
- **Future directions:**
  - Optimize Jolt for ML primitives and leverage parallel hardware.
  - Integrate robust aggregation or anomaly detection with verifiable proofs.
  - Explore recursive aggregation of many Jolt-FL proofs using folding schemes.
  - Closer integration between zkVM toolchains and mainstream ML frameworks.

Takeaways & Q&A

- Jolt-FL shows that **general-purpose zkVMs** can support verifiable FL, not just hand-crafted circuits.
- We provide **strong integrity guarantees**: every accepted update is backed by a ZK proof of correct training.
- Our prototype on MNIST demonstrates:
  - Modest proof sizes and fast verification.
  - 10–15$\times$ prover overhead with preserved accuracy.
  - Robustness against a high fraction of malicious clients.
- **Big picture:** zkVM-based zkML is a promising direction for trustworthy, privacy-preserving distributed learning.

Thank you!

Questions and discussions are very welcome.

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