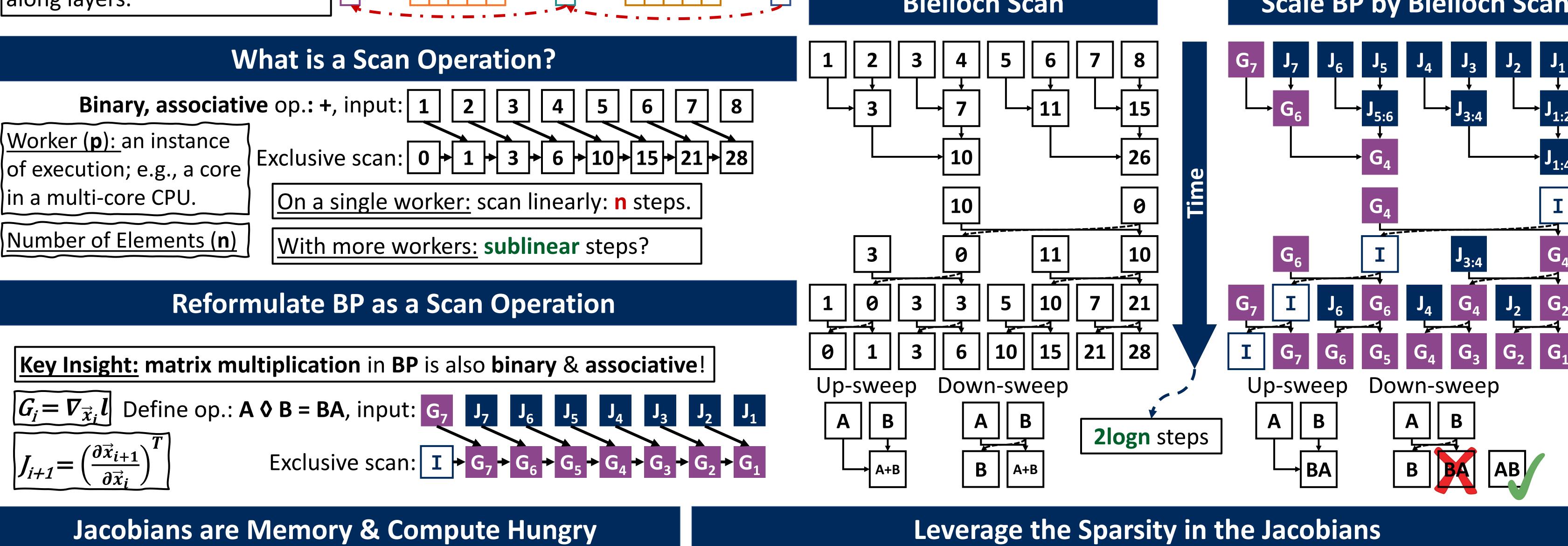
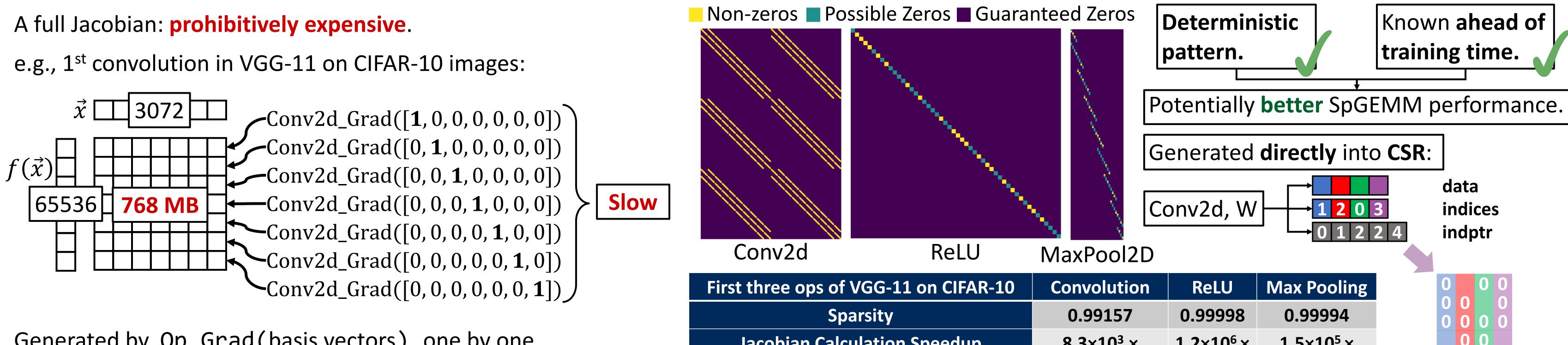
Scaling Back-Propagation by Parallel Scan Algorithm Shang Wang^{1,2} | Yifan Bai¹ | Gennady Pekhimenko^{1,2} **VECTOR** Computer Science UNIVERSITY OF TORONTO Back-propagation (BP)'s Strong Sequential Dependency **Model Parallel Training** Strong sequential dependency limits scalability on parallel systems. → Linear ReLU Linear Loss **Pipeline Parallel Training:** $f(\vec{x})$ Linear per-device space $\partial \vec{x}$ complexity. "Bubble of idleness" $\nabla_{f(\vec{x})}l$ vs. convergence affect. **Backward Pass Strong Sequential Dependency** along layers. **Blelloch Scan** Scale BP by Blelloch Scan





Generated by Op_Grad(basis vectors) one by one. $8.3 \times 10^3 \times$ **Jacobian Calculation Speedup** $1.2\times10^6\times$ $1.5 \times 10^{5} \times$

Evaluation Backward Pass Speedup over the Baseline Model: RNN Task: Bitstream Classification Hardware Sensitivity 108× 100 ■ 2070 ■ 2080Ti Speedup g 25 Baseline: PyTorch Autograd & cuDNN Latency 0 2 0 Hardware: **RTX 2070** & **RTX 2080Ti** 10k 30k Implementation: Custom CUDA Kernels Sequence Length **T** (reflecting **n**) Sequence Length T End-to-end training when 16 Latency (ms) per Iteration O 1 1 1 0 2 0 Batch Size (B) = 16, Sequence Length (T) = 1000Baseline —BPPSA 8 2.4 Speedup 2.17× Speedup 1/256 1/128 1/64 1/32 1/16 1/8 1/4 1/2 1/256 1/128 1/64 1/32 1/16 1/8

Fraction of GPU per Sample **1/B** (reflecting **p**)

BPPSA scales with n until being

bounded by **p**; and **scales** with **p**.

5000

1000

2000

3000

Wall-clock Time (s)

BPPSA reconstructs the original BP exactly.

4000

Fraction of GPU per Sample (1/B)

| # of SMs(2080Ti) > # of SMs(2070) |

→ Latency(2080Ti) < Latency(2070).