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Optimizing Deep Learning Systems for Hardware

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Part IV : System-level Optimization

- PIV.a : Parallelism
- PIV.b : Mixed-Precision Training
- PIV.c : Other

Mixed-Precision Training

- Use lower-precision data types (e.g., FP16 or BF16) for parts of model training instead of full 32-bit (FP32) floats.
- Combines:
  - FP16/BF16 for compute-intensive operations
  - FP32 for numerically sensitive operations (e.g., loss scaling, weight updates)
- You need Tools/frameworks:
  - NVIDIA AMP (Automatic Mixed Precision),
  - PyTorch native amp,
  - TensorFlow mixed_precision API.

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Is it system-level really?

- When we quantized models it was model level?
- Yes. This time it is different.

Model-Level	**System-Level**
Changes the network architecture	**Keeps model architecture the same**
Requires ML domain knowledge	**Requires hardware/runtime knowledge**
Quantization Frameworks	**Mixed-Precision Frameworks**

Is it system-level really?

- Mixed-precision training does not alter the model structure or algorithm.
- It's an implementation detail handled by the training framework and hardware stack.

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Changes the network architecture	**Keeps model architecture the same**
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Quantization Frameworks	**Mixed-Precision Frameworks**

Benefits

- Faster Training Throughput
  - FP16 and BF16 operations are up to 2x–8x faster on modern GPUs (e.g., NVIDIA Tensor Cores)
- Lower Memory Footprint
  - Reduced precision cuts memory usage nearly in half
  - Enables larger batch sizes, deeper models
- Better Hardware Utilization
  - Takes advantage of specialized hardware (e.g., Tensor Cores on NVIDIA, BF16 on TPUs)

How it works:

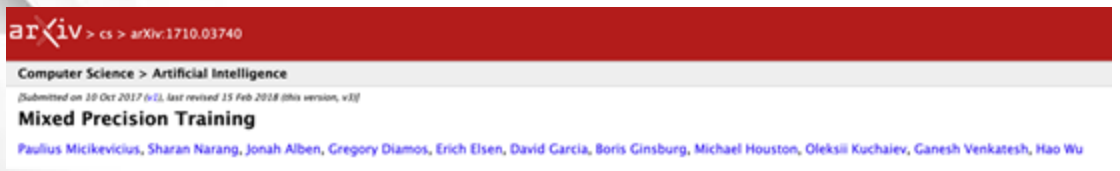
- Handled by Compiler/runtime stack
  - GPU drivers and libraries
  - Training loop wrappers — *not by the model author*


Model remains unchanged


System handles casting, scaling, kernel selection


Benefit comes from exploiting hardware and software stack

How it works:



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- This diagram illustrates how mixed-precision training works for a single layer during a training iteration. It shows:
  - Which parts of the computation use FP16 (half precision)
  - Which parts are kept in FP32 (full precision)
  - How data flows between forward pass, backward pass, and weight update steps

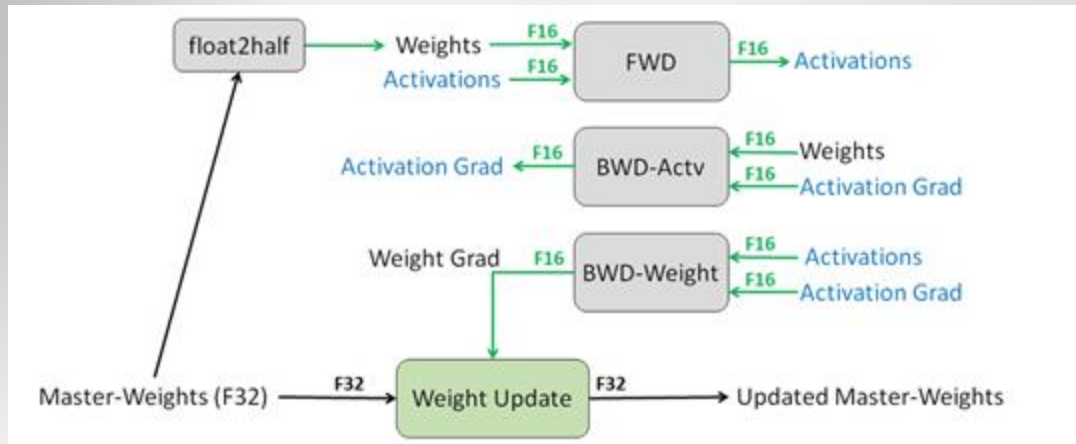
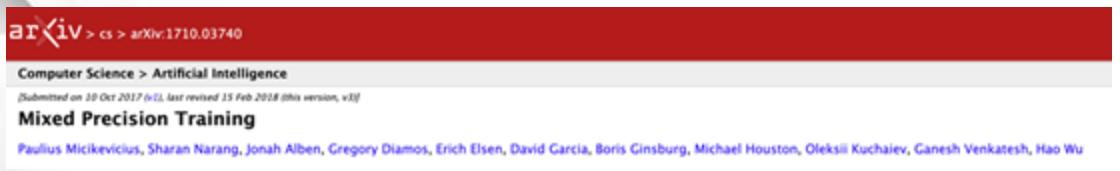
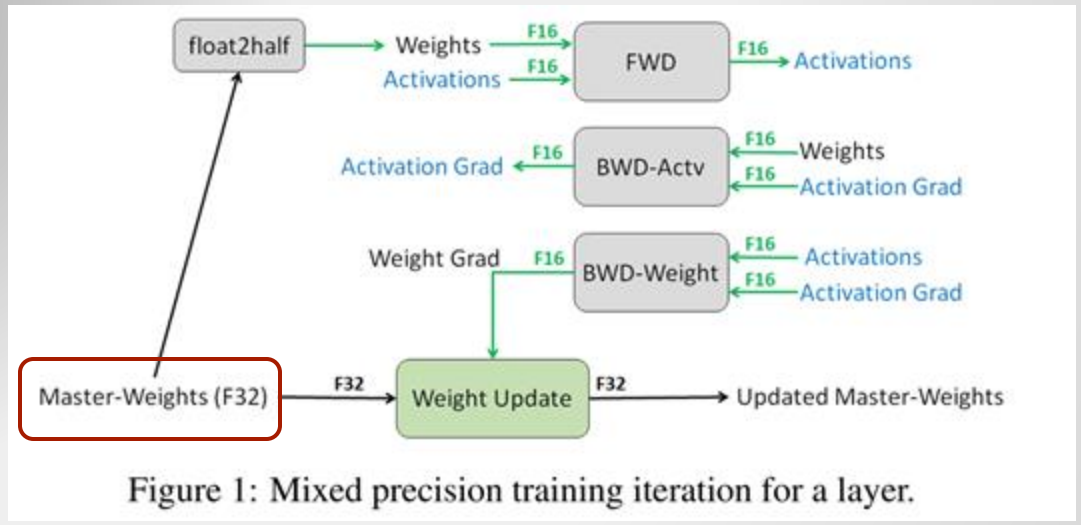


Figure 1: Mixed precision training iteration for a layer.

Components



- Master Weights (F32)
  - The main copy of the model's weights is stored in FP32.
  - These are not used directly for forward/backward passes, but only for updates.
  - They are converted to FP16 before being used for computation.



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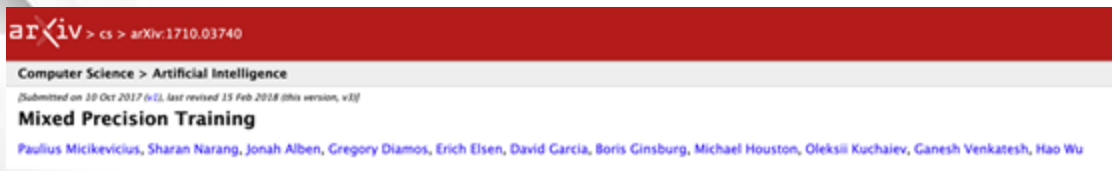
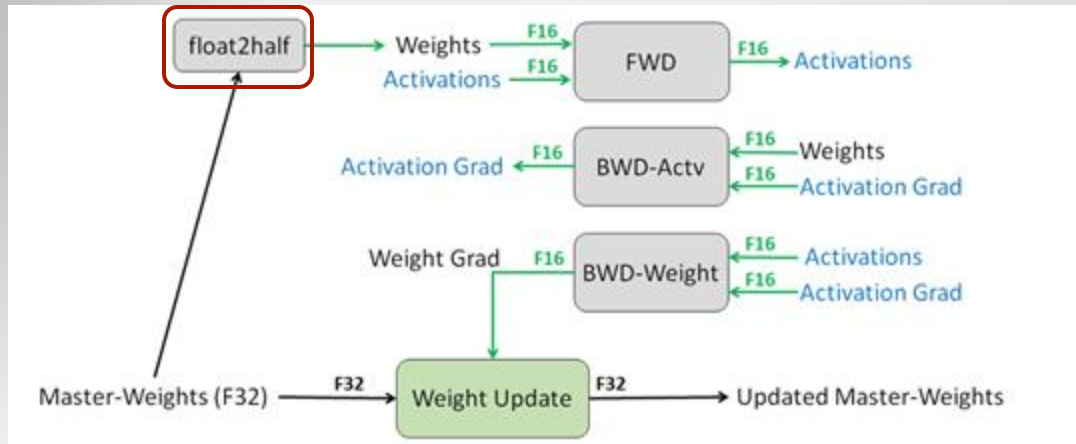


- float2half
  - This block converts FP32 master weights to FP16 weights.
  - These FP16 weights are then used in the forward and backward passes.



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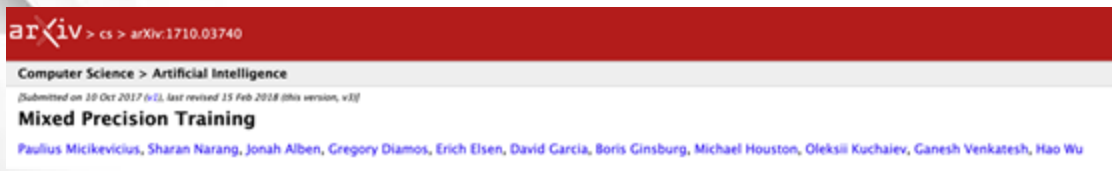
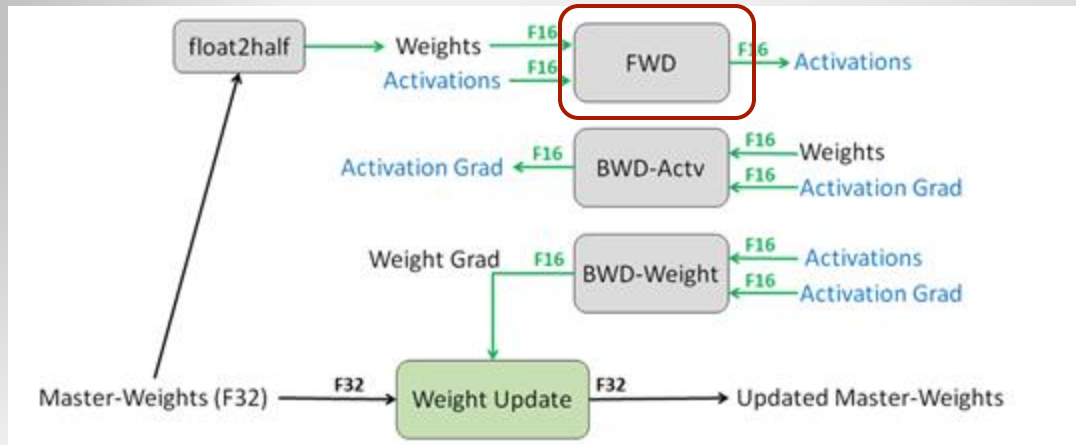


- FWD (Forward Pass)
  - Inputs: FP16 weights and FP16 activations
  - Outputs: FP16 activations
- This is where the model computes the layer outputs from inputs.
- All done in FP16 for speed and lower memory usage.



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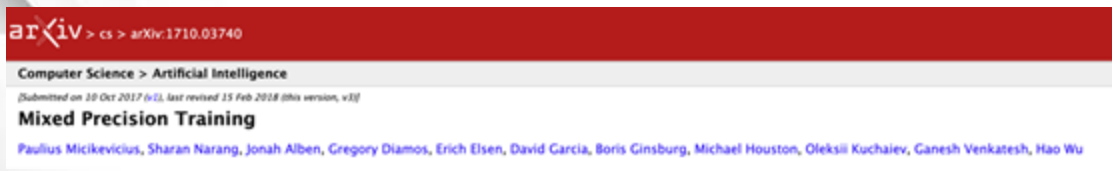


- BWD-Actv (Backward Pass – Activation Gradient)
  - Computes gradients of the loss w.r.t. activations.
  - Takes in:
    - FP16 weights
    - FP16 gradients of outputs (activation grad)
  - Outputs:
    - FP16 gradients of inputs

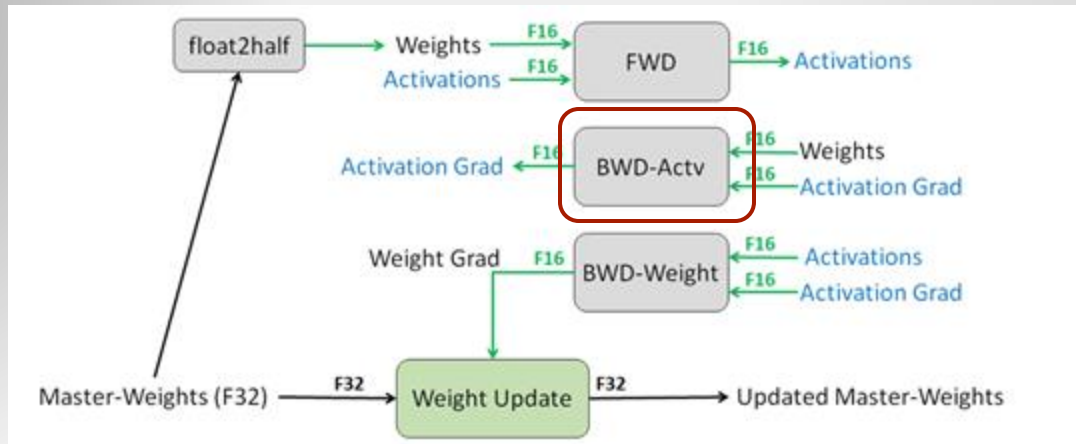
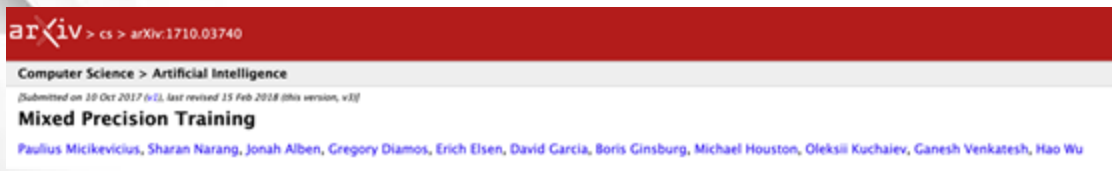


Figure 1: Mixed precision training iteration for a layer.

Components



- BWD-Weight (Backward Pass – Weight Gradient)
  - Computes gradients w.r.t. weights.
  - Takes in:
    - FP16 activations (from FWD)
    - FP16 activation gradients
  - Outputs:
    - FP16 weight gradients

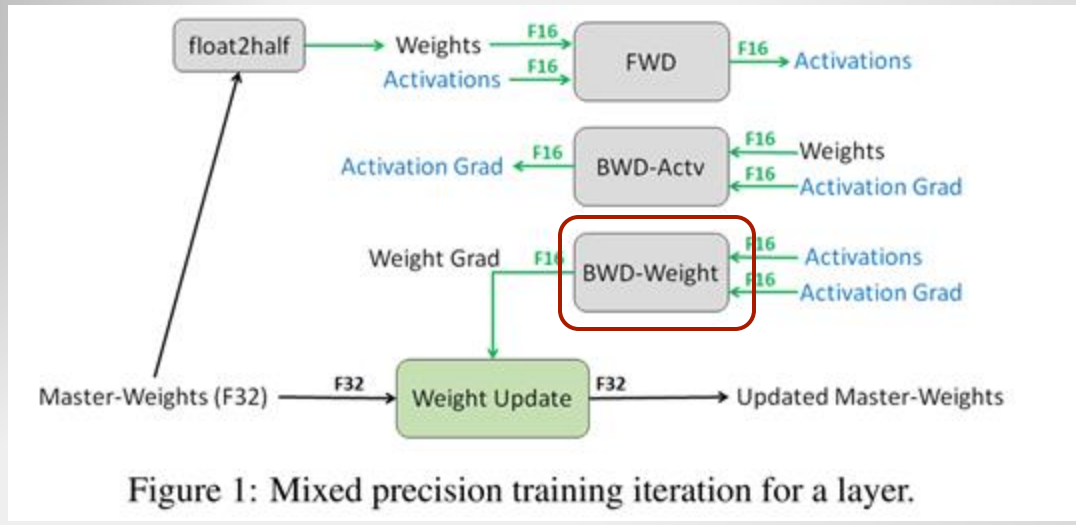
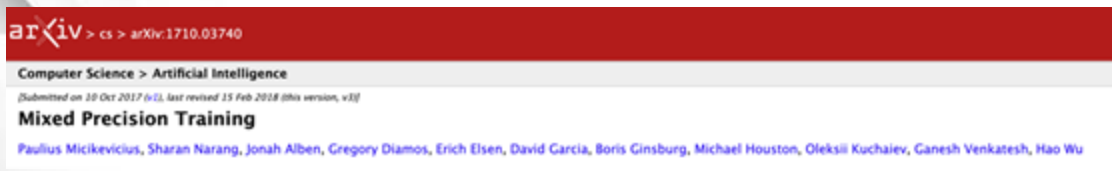


Figure 1: Mixed precision training iteration for a layer.

Components



- Weight Update
  - The FP16 weight gradients are converted to FP32 and used to update the FP32 master weights.
  - The update is performed in full precision for numerical stability.
  - The updated weights are then reused in the next iteration.

Figure 1: Mixed precision training iteration for a layer.

Components

arXiv > cs > arXiv:1710.03740

Computer Science > Artificial Intelligence

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Mixed Precision Training

Paulius Micikevicius, Sharan Narang, Jonah Alben, Gregory Diamos, Erich Elsen, David Garcia, Boris Ginsburg, Michael Houston, Oleksii Kuchaiev, Ganesh Venkatesh, Hao Wu

- Task: English-to-French translation
  - Model: 3-layer LSTM with attention (3×1024 LSTM)
- Comparison between:
  - Full precision (FP32) training runs (ref1, ref2, ref3)
  - Mixed-precision training with two different loss scaling values

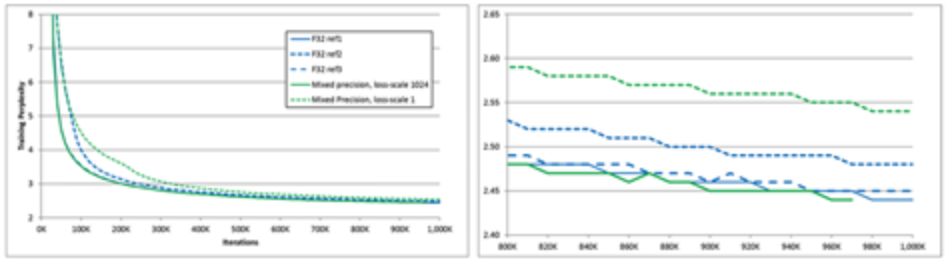
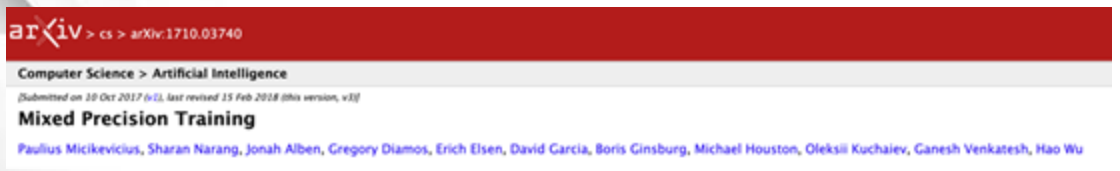
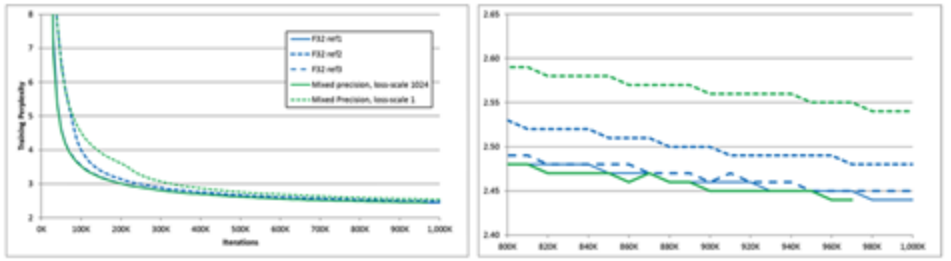


Figure 4: English to French translation network training perplexity, 3x1024 LSTM model with attention. Ref1, ref2 and ref3 represent three different FP32 training runs.

Components



- Left: Training perplexity over iterations
  - Mixed-precision (green solid line, loss scale = 1024) shows faster convergence than FP32
  - Poorer performance without proper loss scaling (green dashed line, scale = 1)
- Right Zoom-In: Final training perplexity
  - Mixed-precision (green solid) matches or slightly outperforms FP32 runs
  - Proper loss scaling is essential for stability and accuracy



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Next: Part IV.c

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Thanks!

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EuroHPC
Joint Undertaking

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