TRAINING WITH MIXED PRECISION

Boris Ginsburg, Sergei Nikolaev, Paulius Micikevicius
bginsburg, pauliusm, snikolaev@nvidia.com

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NVIDIA.

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and

cuDNN team

This work is based on NVIDIA branch of caffe
https://github.com/NVIDIA/caffe (caffe-0.16)

AGENDA

1. Mixed precision training with Volta TensorOps
2. More aggressive training methods
    - FP16 training
    - FP16 master weights
3. Nvcaffe float16 internals

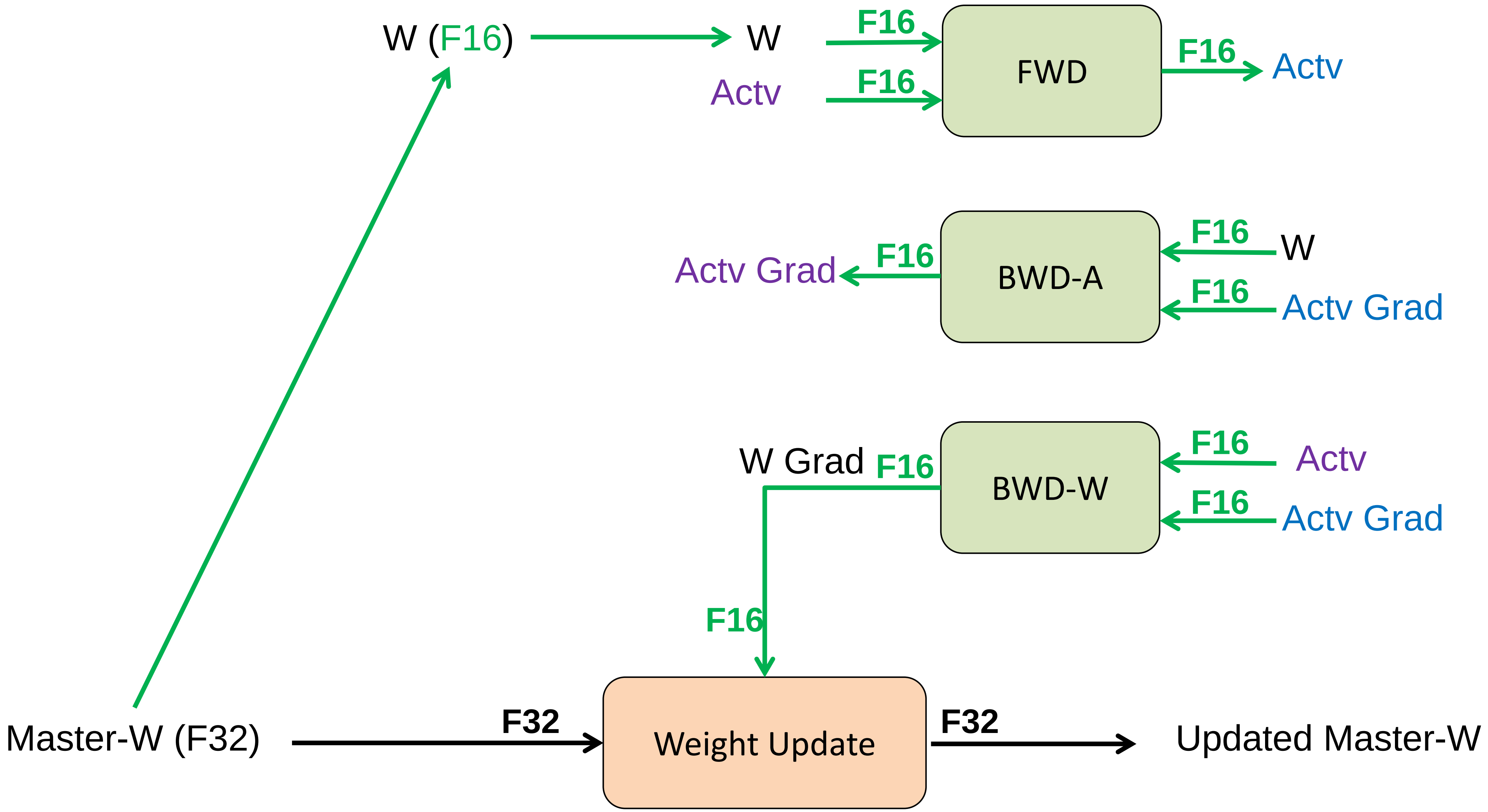
SOME TERMINOLOGY

Training values storage	Matrix-Mult Accumulator	Name
FP32	FP32	FP32 training
FP16	FP32	Mixed precision training
FP16	FP16	FP16 training

With mixed or FP16 training, master weights can be FP16 or FP32.

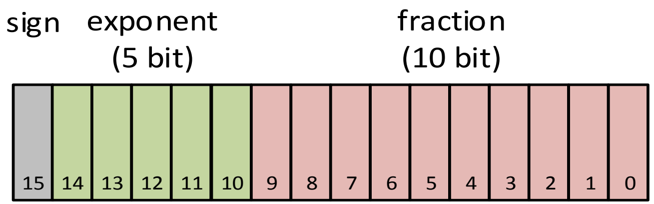
Volta: **Mixed precision training** with **FP32 master weight storage**.

VOLTA TRAINING METHOD

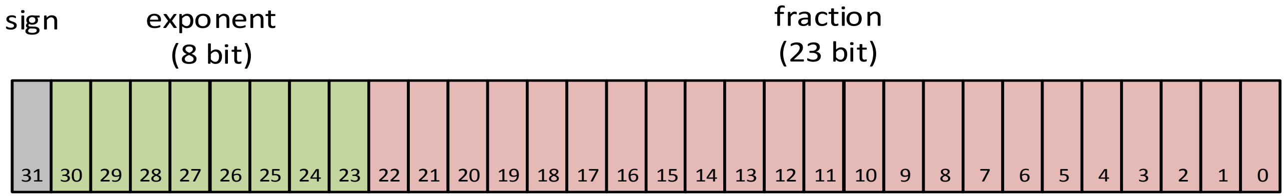


HALF-PRECISION FLOAT (FLOAT16)

float16

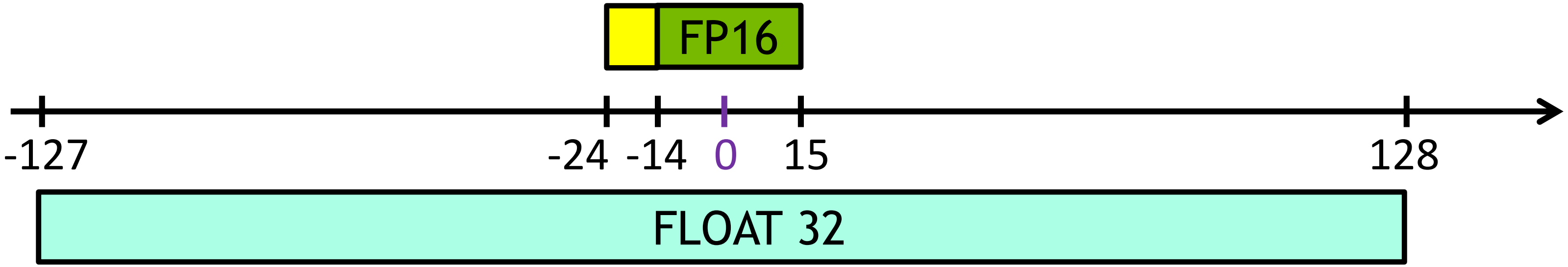


float

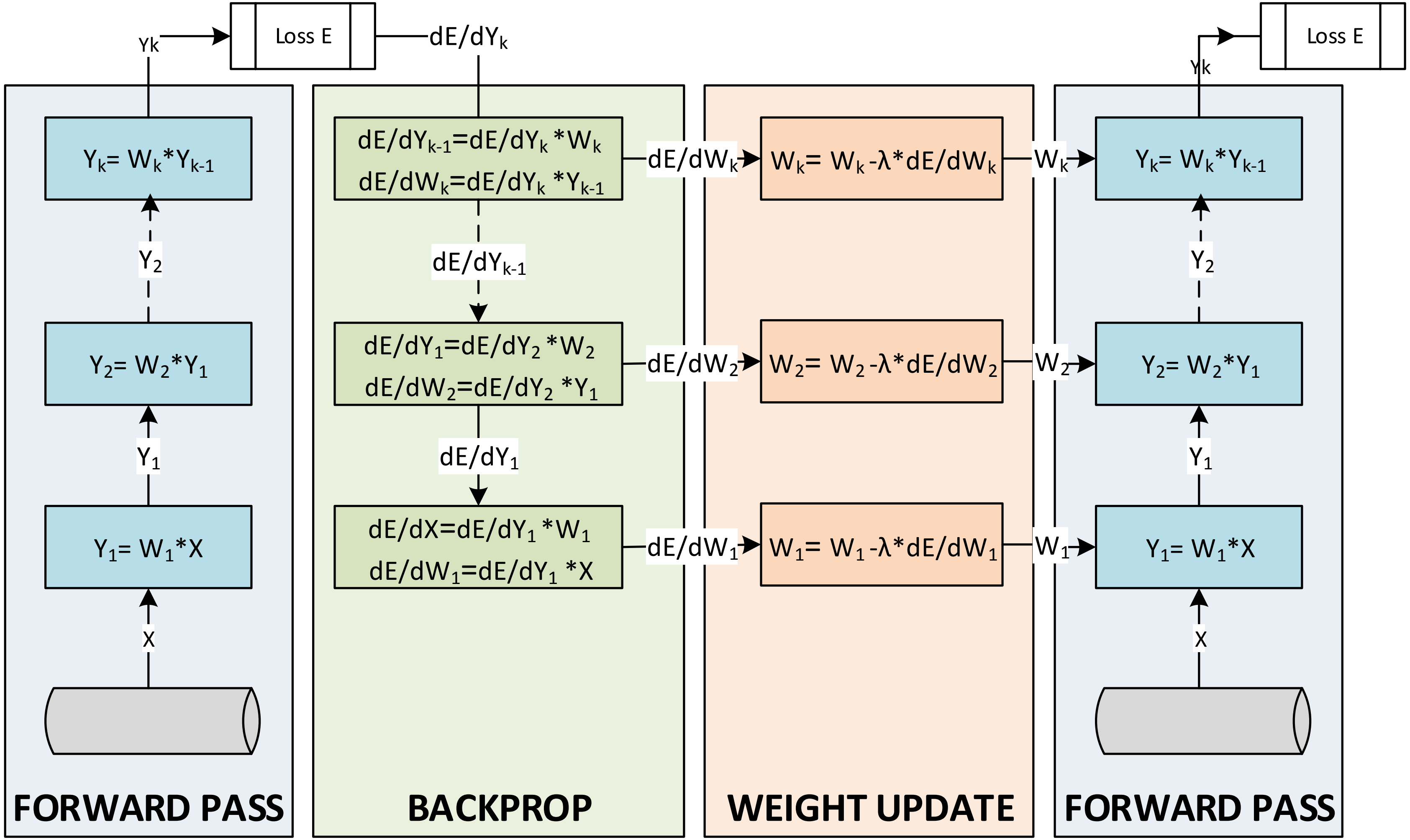


FLOAT16 has wide range (2^{40}) … but not as wide as FP32!

Normal range: [6×10^{-5} , 65504]
Sub-normal range: [6×10^{-8} , 6×10^{-5}]



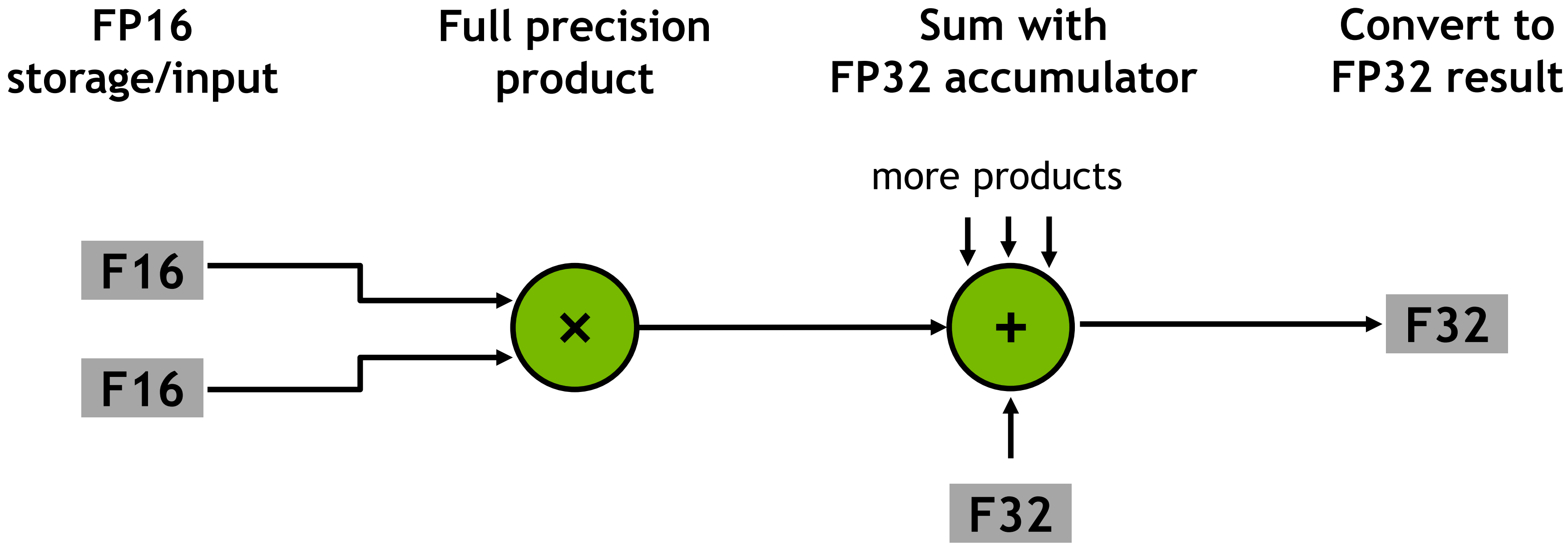
TRAINING FLOW



TENSOR CORE 4X4X4 MATRIX-MULTIPLY ACC

$$\underset{\text{FP16 or FP32}}{D} = \underset{\text{FP16}}{\begin{pmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{pmatrix}} \underset{\text{FP16}}{\begin{pmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{pmatrix}} + \underset{\text{FP16 or FP32}}{\begin{pmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{pmatrix}}$$

VOLTA TENSOR OPERATION



Also supports FP16 accumulator mode for inferencing

SOME NETWORKS TRAINED OUT OF THE BOX

TensorOp training matched the results of F32 training

- Same hyper-parameters as F32
- Same solver and training schedule as F32

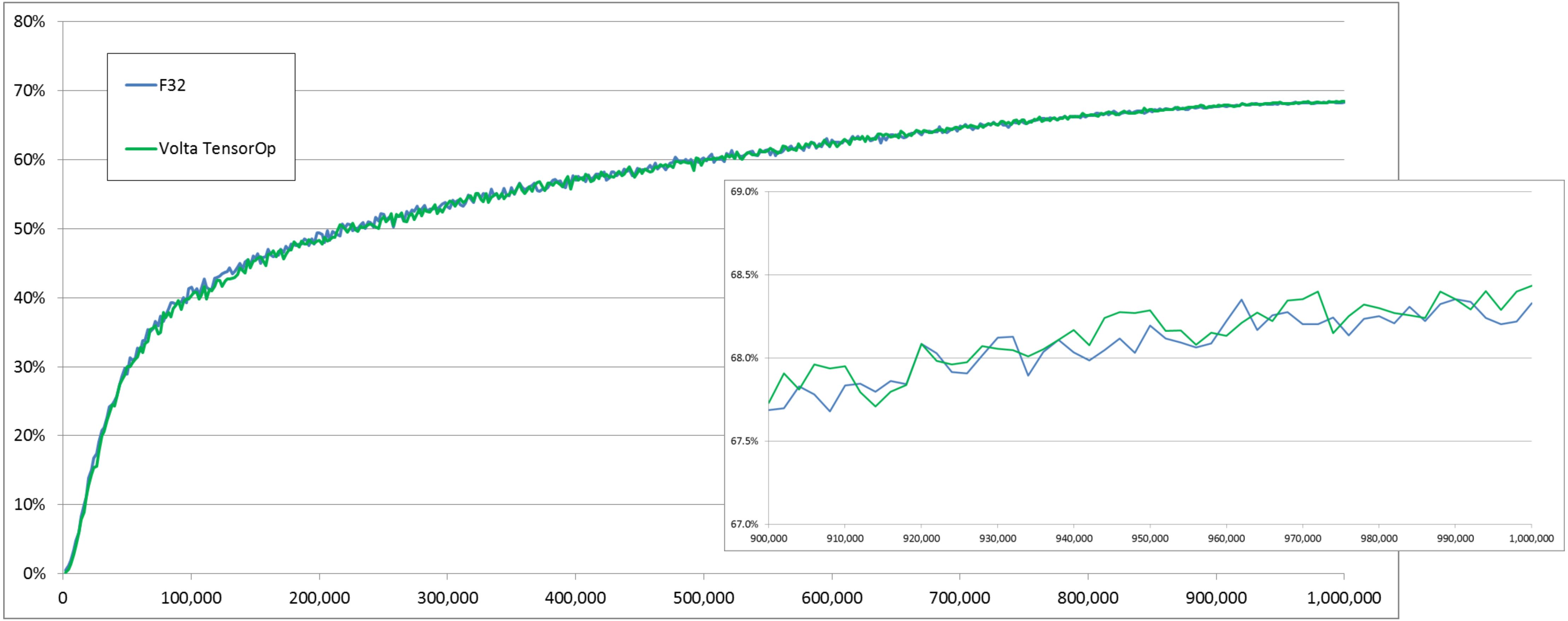
Image classification nets (trained on ILSVRC12):

- No batch norm: GoogLeNet, VGG-D
- With batch norm: Inception v1, Resnet50
- All used SGD with momentum solver

GAN

- DCGAN-based, 8-layer generator, 7-layer discriminator
- Used Adam solver

GOOGLENET



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0%
F32
Volta TensorOp
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67.0%
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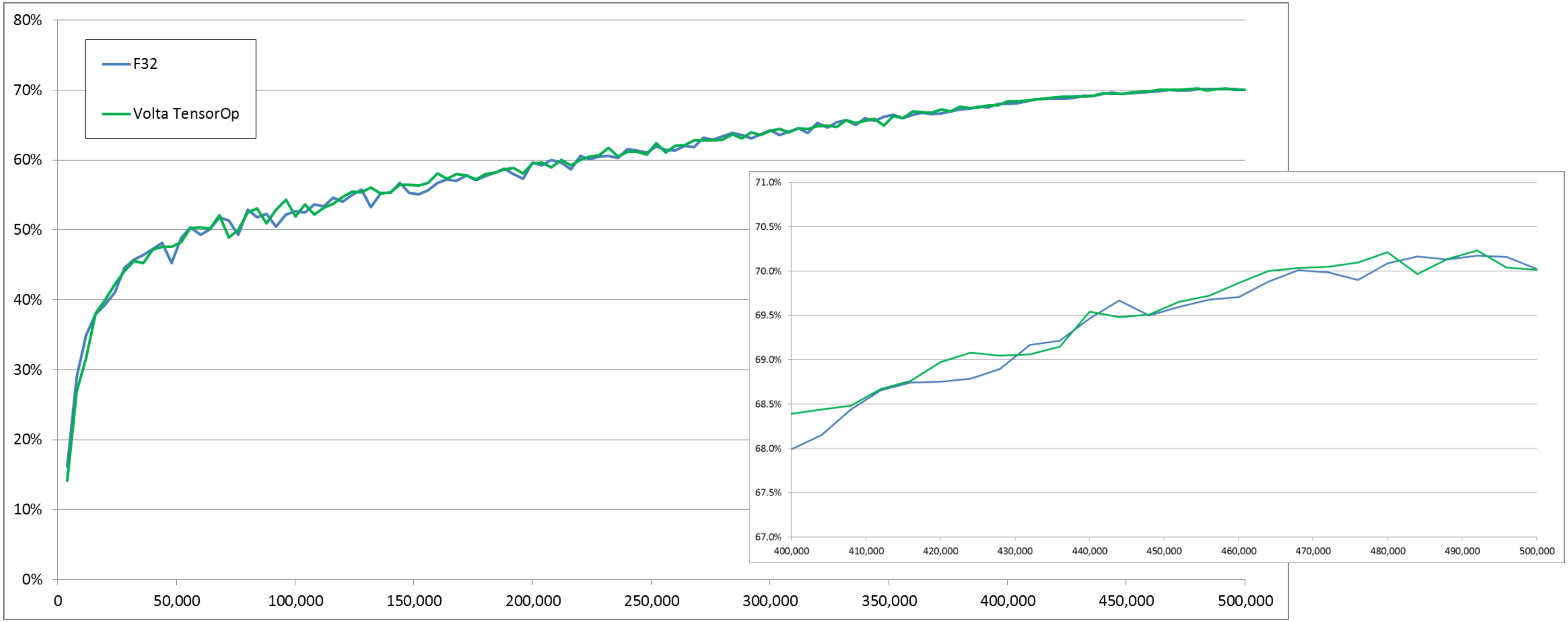
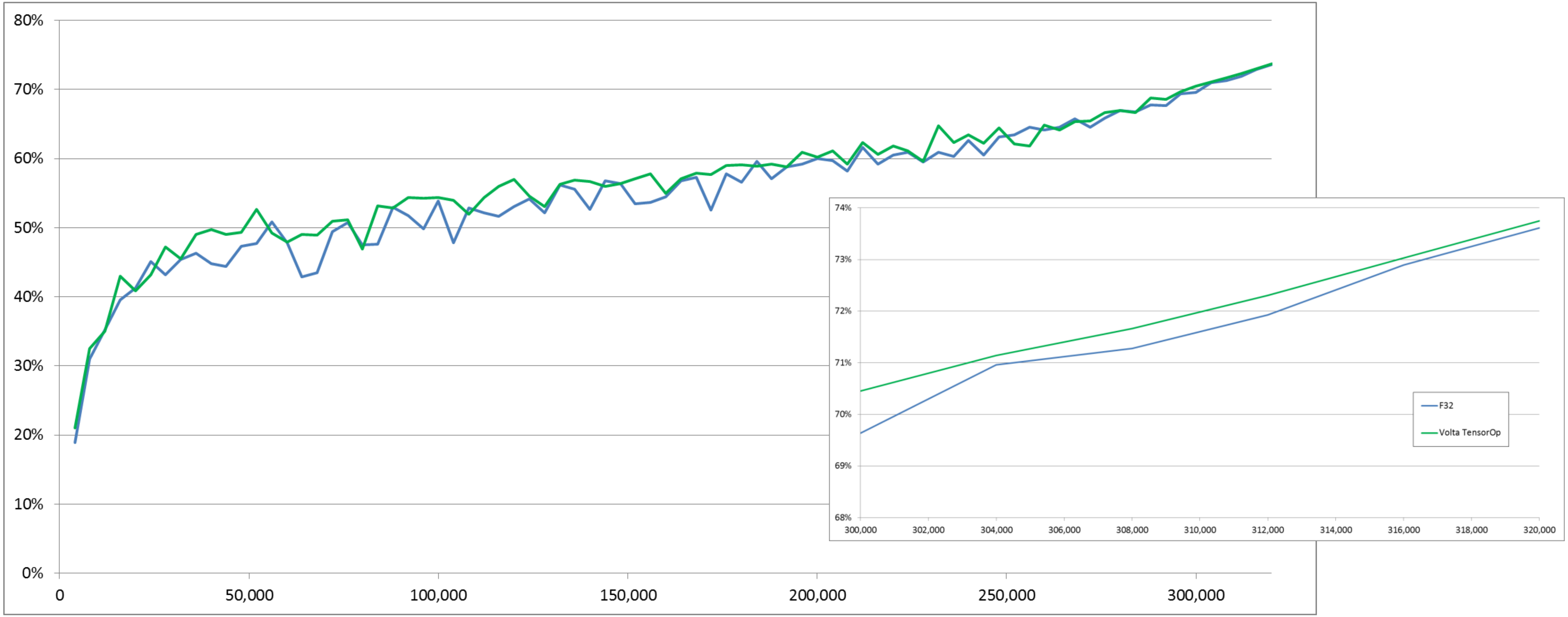
INCEPTION V1



RESNET50



80%
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71%
70%
69%
68%
300,000
302,000
304,000
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308,000
310,000
312,000
314,000
316,000
318,000
320,000
F32
Volta TensorOp

SOME NETWORKS NEEDED HELP

Networks:

- Image classification: CaffeNet
  - Was not learning out of the box, even with F32 math when storage is F16
- Detection nets:
  - Multibox SSD with VGG-D backbone
    - Was not learning, even with F32 math when storage is F16
  - Faster R-CNN with VGG-D backbone
    - 68.5% mAP, compared to 69.1% mAP with F32
- Recurrent nets:
  - Seq2seq with attention: lagged behind F32 in perplexity
  - bigLSTM: diverged after some training

Remedy in all the cases: scale the loss value to “shift” gradients

LOSS SCALING

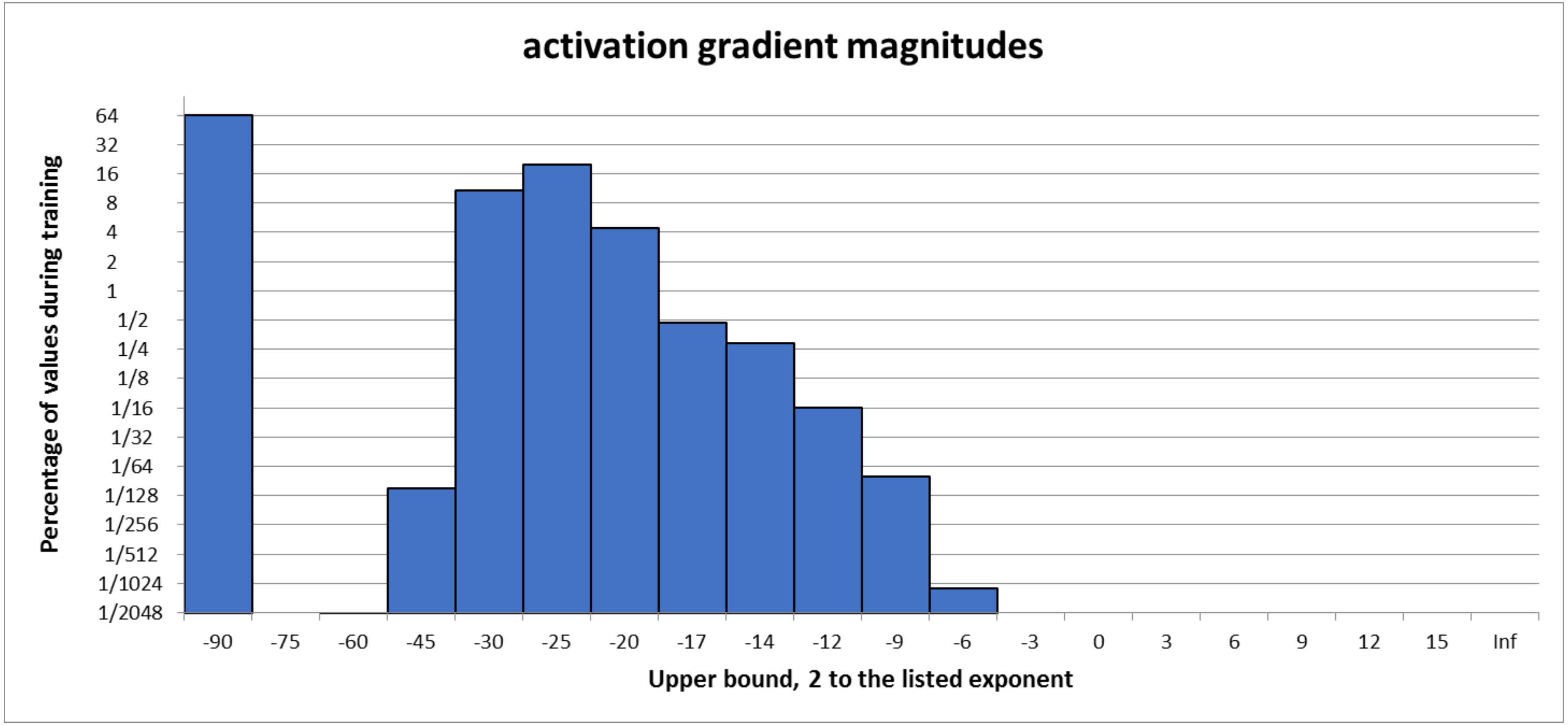
To shift gradients dE/dX we will scale up the loss function by constant (e.g. by 1000):

```
layer {
  type: "SoftmaxWithLoss"
  loss_weight: 1000.
}
```

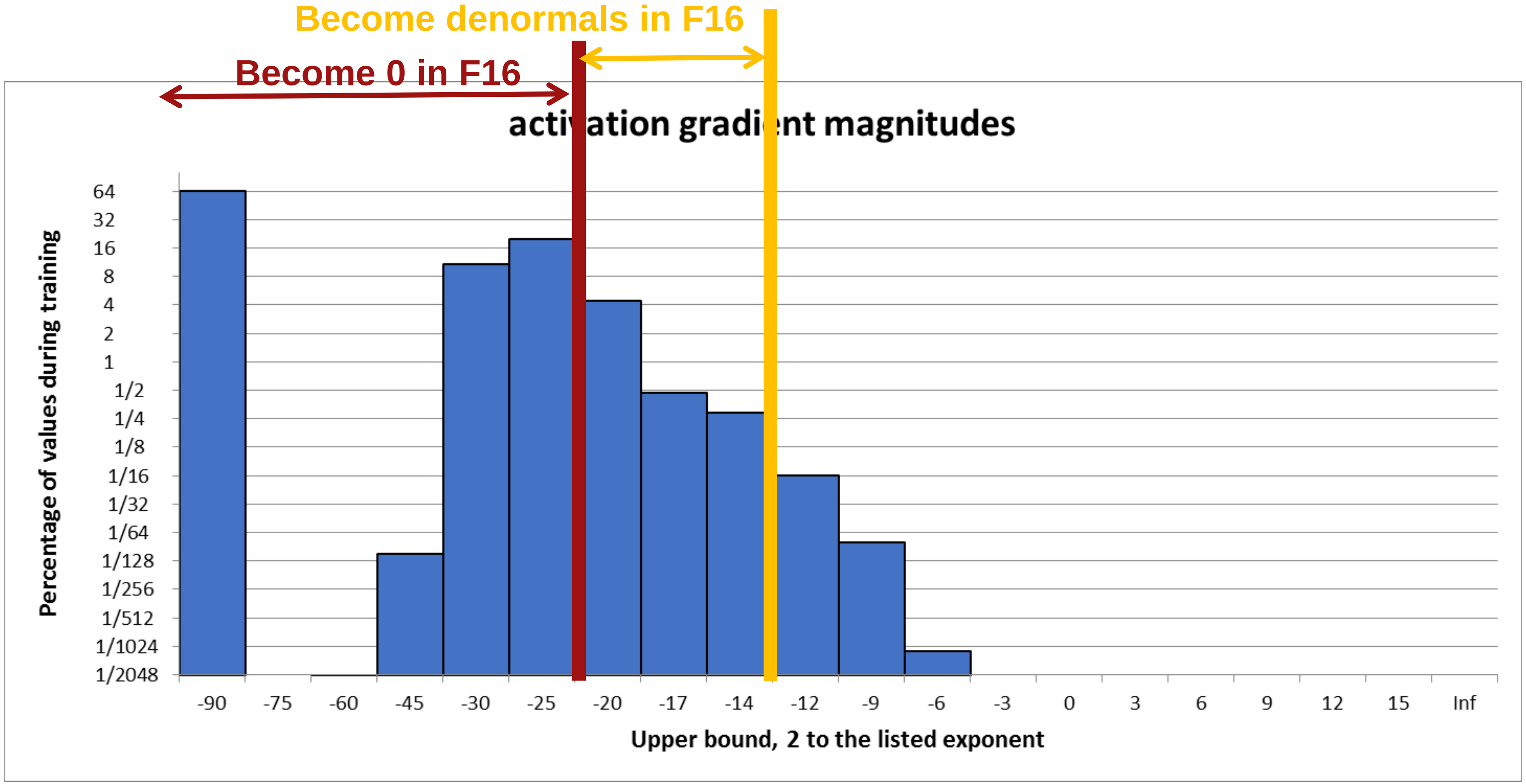
and adjust learning rate and weight decay accordingly:

```
base_lr: 0.01 0.00001              #    0.01 / 1000
weight_decay: 0.0005 0.5           # 0.0005 * 1000
```

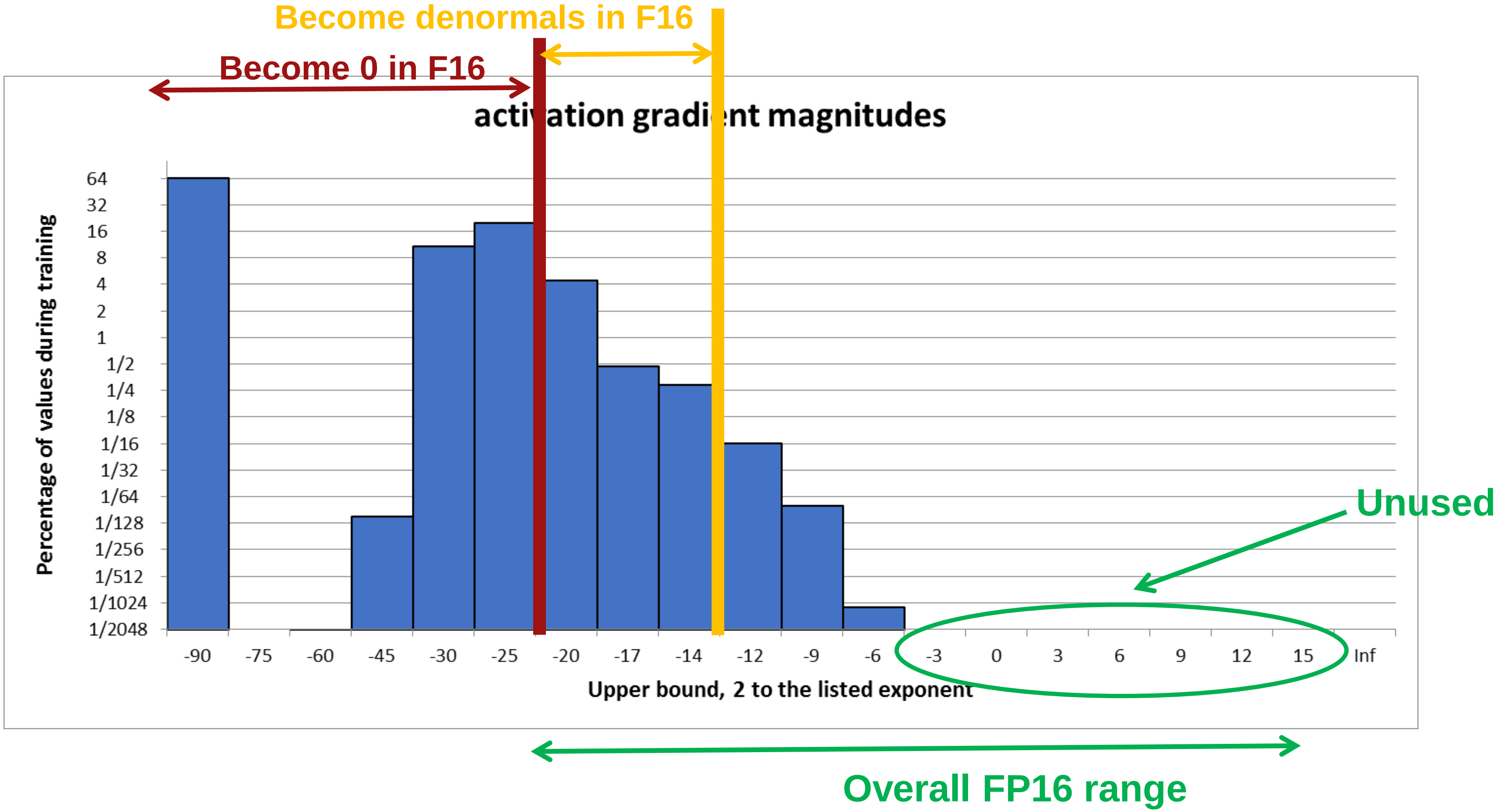
MULTIBOX SSD: ACTIVATION GRADIENT MAGNITUDE HISTOGRAM



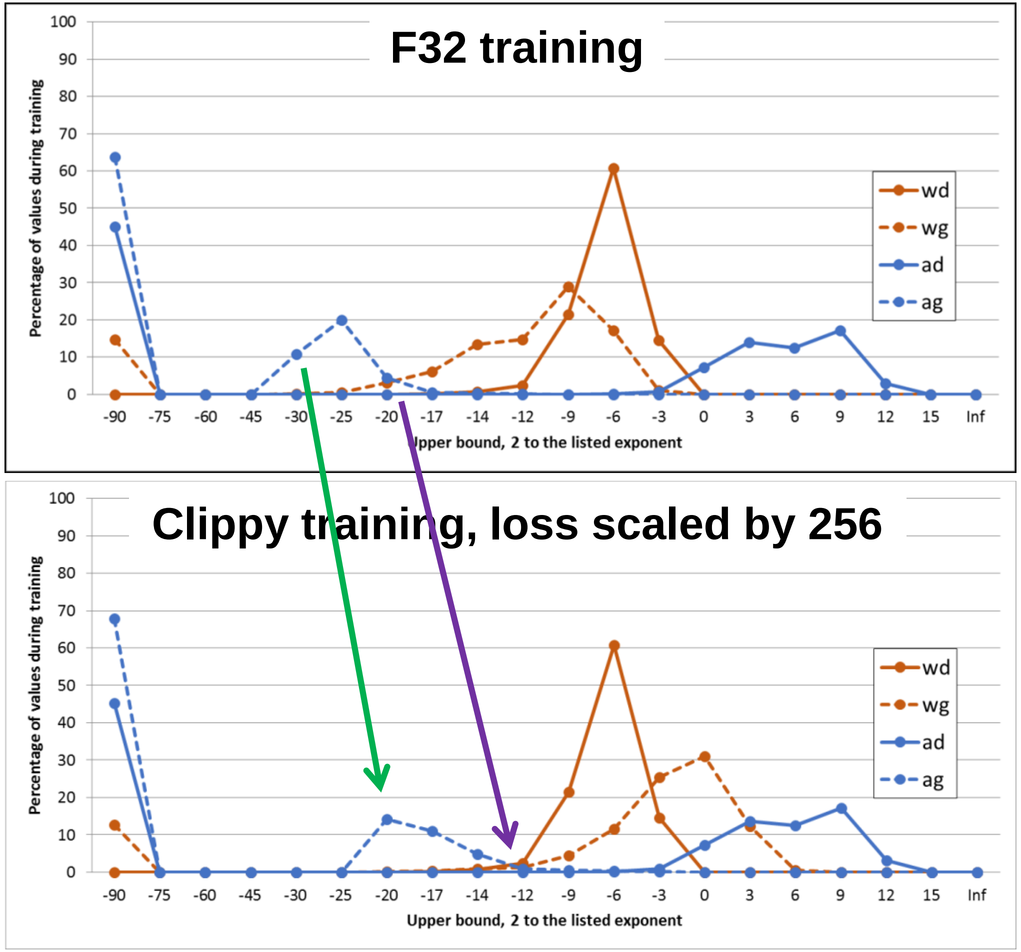
MULTIBOX SSD: ACTIVATION GRADIENT MAGNITUDE HISTOGRAM



MULTIBOX SSD: ACTIVATION GRADIENT MAGNITUDE HISTOGRAM



MULTIBOX: SCALING LOSS AND GRADIENTS



Loss scaled by 256

- Consequently, gradients get scaled by 256
- By chain rule

Benefits:

- Hardly any activation gradients become 0 in F16
- Most weight gradients become normalized values in F16

DETECTION TRAINING RESULTS

Multibox-SSD mAP:

F32: 76.9%

F16: 77.1%, loss scaled by 256

Without scaling: doesn't learn

TensorOp: in flight

matching F32 at 74.1% mAP halfway through training

Faster-RCNN mAP:

F32: 69.1%

TensorOp: 69.7%, loss scaled by 256, without loss-scaling: 68.5%

SEQ2SEQ TRANSLATION NETWORK

WMT15 English to French Translation

seq2seq networks with attention:

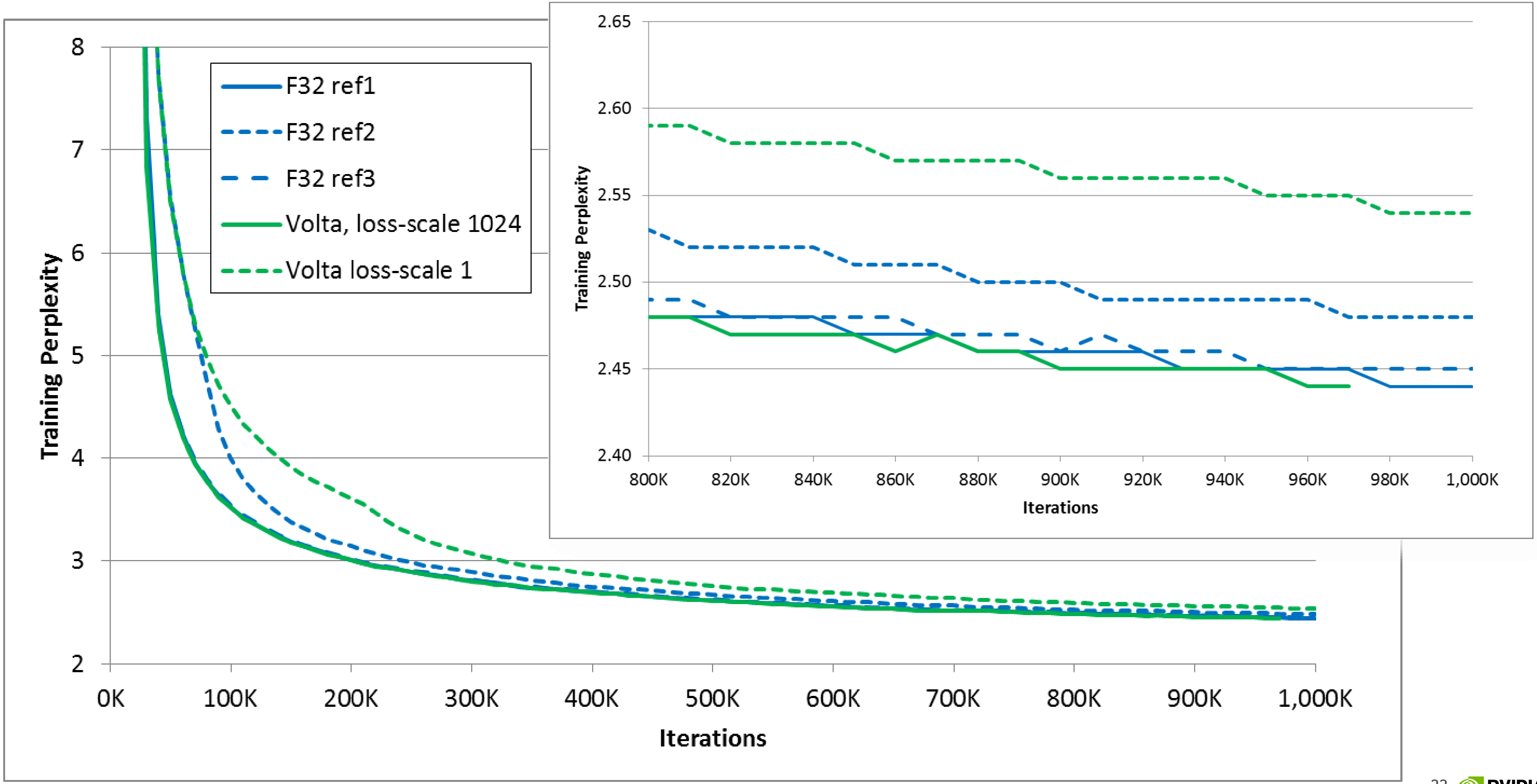
- Based on TensorFlow tutorial
- 3x1024 LSTM
- 5x1024 LSTM

Word vocabularies:

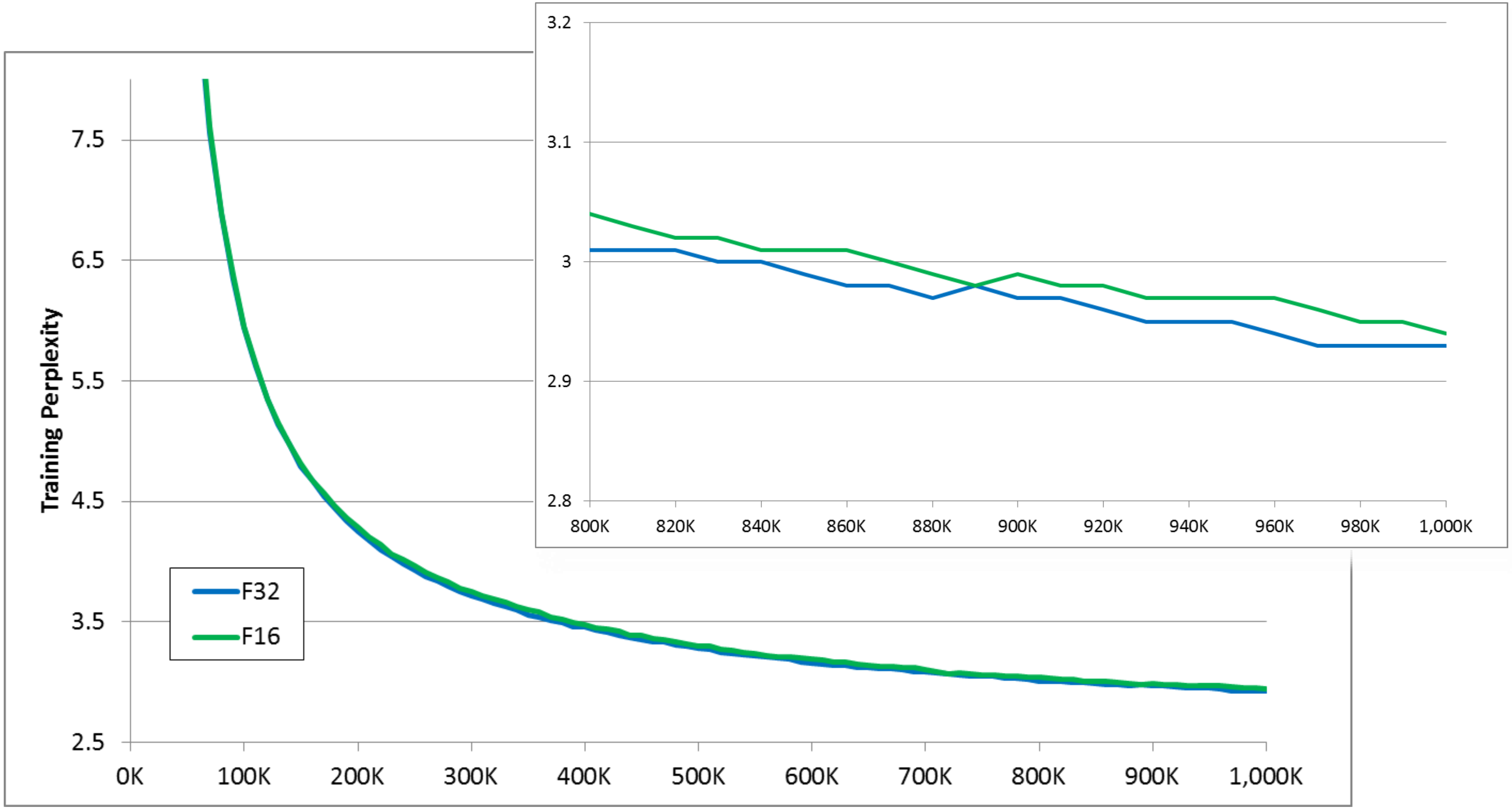
- 100K English
- 40K French

SGD solver

SEQ2SEQ: 3X1024 LSTM



SEQ2SEQ: 5X1024 LSTM



LANGUAGE MODEL

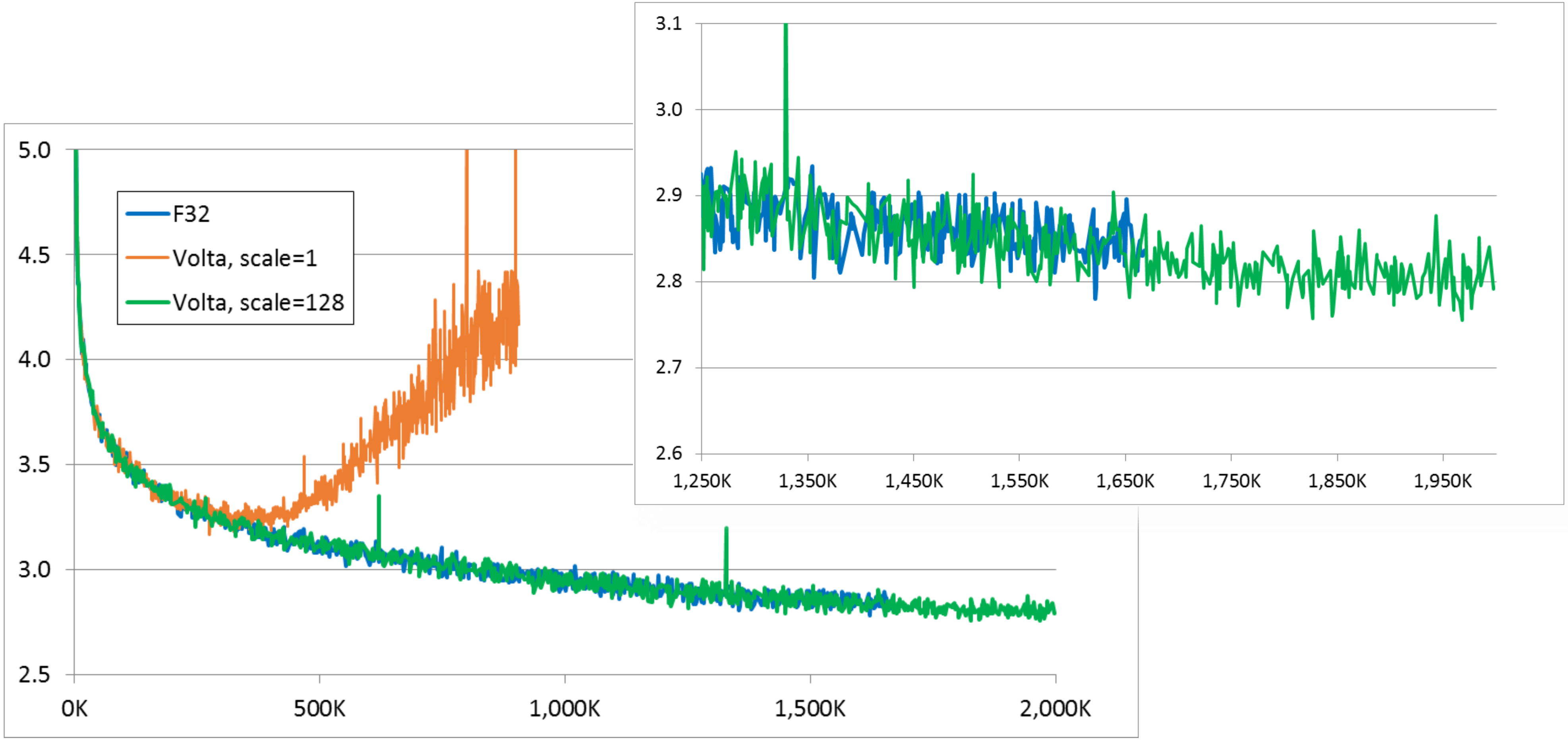
1 Billion Word Language Benchmark

BigLSTM:

- Based on “Exploring the Limits of Language Modeling”
  - https://arxiv.org/abs/1602.02410
- 2x8192 LSTM, 1024 Projection
  - Plus a few variants
- 800K word vocabulary

Adagrad solver

BIGLSTM: 2X8192 LSTM, 1024 PROJECTION



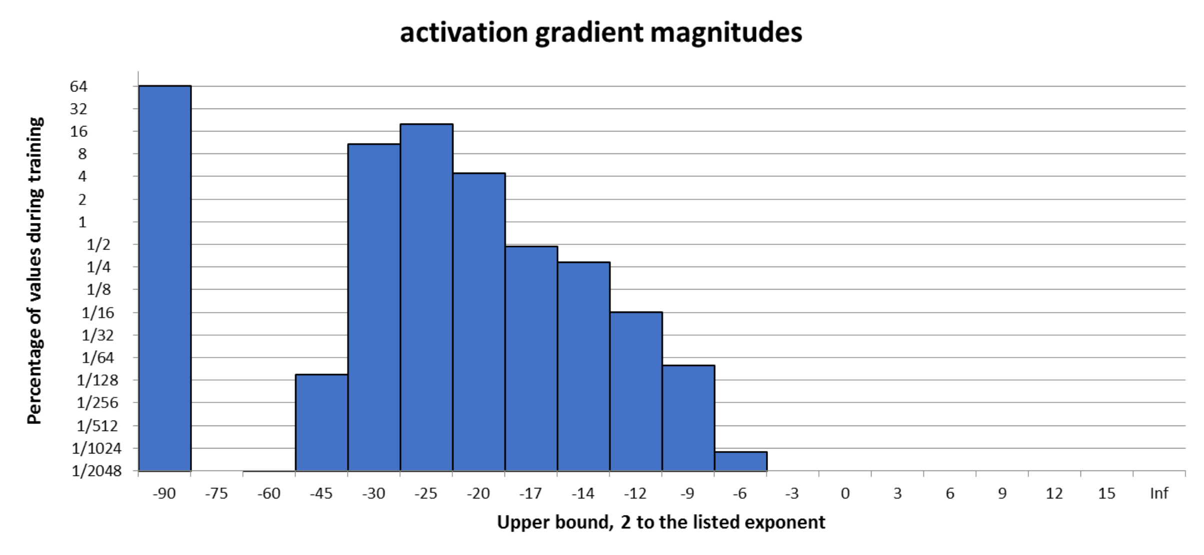
Guidelines for Training with Mixed Precision / TensorOps

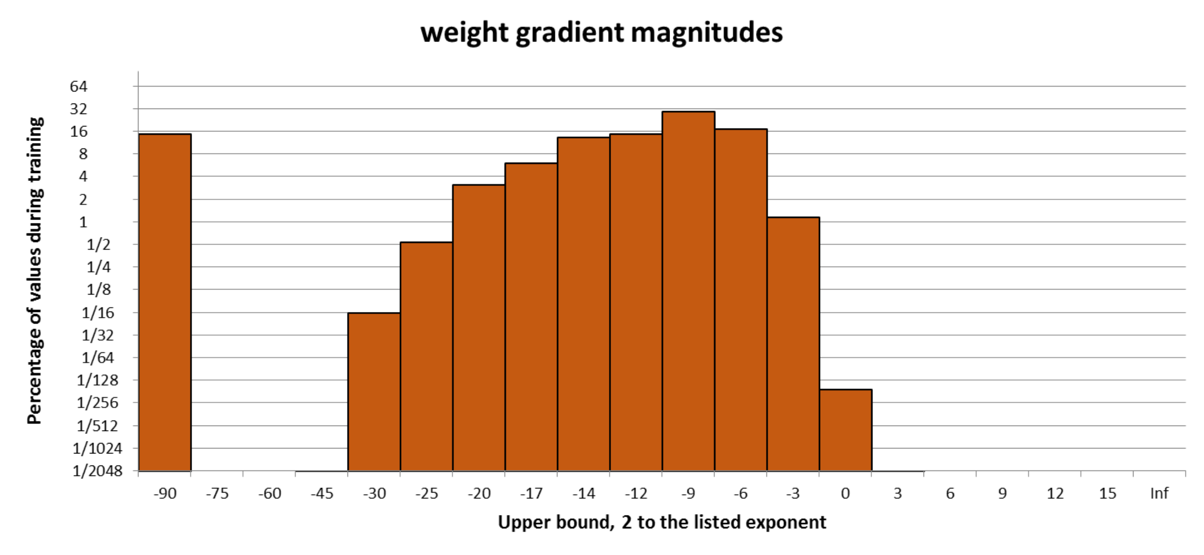
TRAINING WITH MIXED PRECISION

- **A number of cases train "out of the box"**
  - F16 storage and TensorOps for fwd/bwd pass: weights, activations, gradients
  - F32 math for Batch Normalization parameters
  - F32 "master-copy" of weights for weights update

- **When out of the box didn't work:**
  - Gradient values were too small when converted to F16
  - Solved in all cases with loss scaling

OBSERVATIONS ON GRADIENT VALUES





FP16 range is large

- 2^{40} including denorms

Gradient range is biased low vs standard FP16 range

- Max magnitude we've seen was $O(2^3)$
- Enables us to "shift" values without overflowing

Maximum magnitudes:

- weight-grad >> activation-grad
- For all the nets we've looked at

PART 2

More aggressive training exploration :

- FP16 training
- FP16 master weight storage

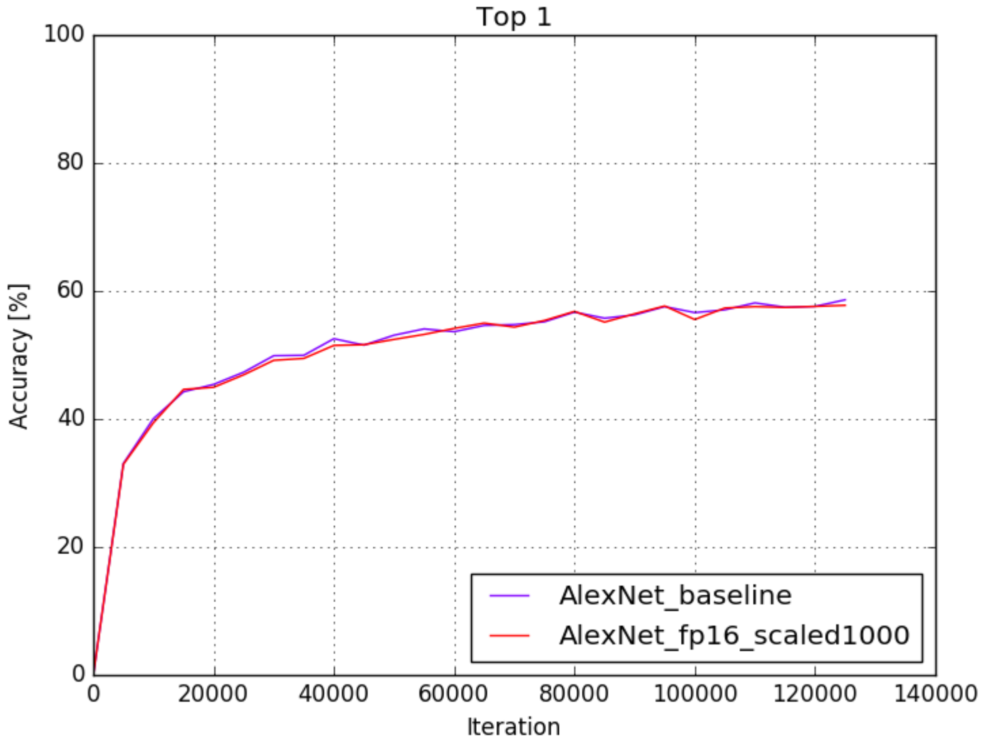
ALEXNET : COMPARISON OF RESULTS

Mode	Top1 accuracy, %	Top5 accuracy, %
Fp32	58.62	81.25
Mixed precision training	58.12	80.71
FP16 training	54.89	78.12
FP16 training, loss scale = 1000	57.76	80.76

Nvcaffe-0.16, DGX-1, SGD with momentum, 100 epochs, batch=1024, no augmentation, 1 crop, 1 model

ALEXNET : FP16 TRAINING WITH SCALING

With loss scale factor = 1000, FP16 training matches other training curves (TensorOp and FP32)



ALEXNET: FP16 MASTER WEIGHT STORAGE

Can we avoid two weights copies? Can FLOAT16 be used for weight update?

“Vanilla” SGD weights update:

$$W(t+1) = W(t) - \lambda * \Delta W(t)$$

If we use float16 for ΔW, the product $\lambda * \Delta W(t)$ can become too small:

- Initially gradients $\Delta W(t)$ are very small. They are multiplied by learning rate λ which is < 1, so $\lambda * \Delta W(t)$ can go into subnormal float16 range

- Later gradients becomes larger, but λ becomes smaller, so $\lambda * \Delta W(t)$ becomes even smaller.

ALEXNET: FP16 MASTER WEIGHT STORAGE

There are a number of solutions for this “vanishing update” problem.

For example to keep two copies of weights: float W_{32} for updates, and float16 W_{16} for forward-backward pass:

Compute $\Delta W_{16}(t)$ using forward-backward pass

Convert gradients to float: $\Delta W_{32}(t) = \mathrm{half2float}(\Delta w_{16}(t))$

Update weights in float: $W_{32}(t+1) = W_{32}(t) - \lambda * \Delta W_{32}(t)$

Make float16 copy of weights: $W_{16}(t+1) = \mathrm{float2half}(W_{32}(t+1))$

Do forward-backward with W_{16} ...

So W_{32} will accumulate small weights updates.

ALEXNET: FP16 MASTER WEIGHT STORAGE

Consider SGD with momentum:

1. Compute momentum H: $H(t+1) = m*H(t) - \lambda*\Delta W(t)$
2. Update weights with H: $W(t+1) = W(t) + H(t+1)$

λ is small, so $\lambda*\Delta W(t)$ can be very small and it can vanish if we compute momentum in float16. Can we fix this?

Denote $D(t)=\Delta W(t)$. Assume for simplicity that λ = const. Then

$$H(t+1) = m*H(t)-\lambda*D(t) = m*(H(t-1)-\lambda*D(t-1)) - \lambda*D(t) =$$

$$-\lambda*\boxed{[\mathbf{D(t) + m*D(t-1) + m^2*D(t-2) + m^k*D(t-k)+}\ldots]}$$

Moment works as average of gradients!

ALEXNET: FP16 MASTER WEIGHT STORAGE

Let's modify the original momentum schema:

1. Compute momentum `H`: `H(t+1)= m*H(t) - λ*ΔW(t)`
2. Update weights with `H`: `W(t+1)= W(t) + H(t+1)`

ALEXNET: FP16 MASTER WEIGHT STORAGE

Let's modify the original momentum schema:

1. Compute momentum G: $G(t+1) = m*G(t) + \cancel{-\lambda} \Delta W(t)$
2. Update weights with G: $W(t+1) = W(t) - \lambda*G(t+1)$

Now G will accumulate average of $\Delta W(t)$ which don't vanish!

Weights update in float16 we use this schema:

Compute $\Delta w_{16}(t)$ using forward-backward pass

Compute momentum: $G_{16}(t+1) = m* G_{16}(t) + \Delta w_{16}(t)$

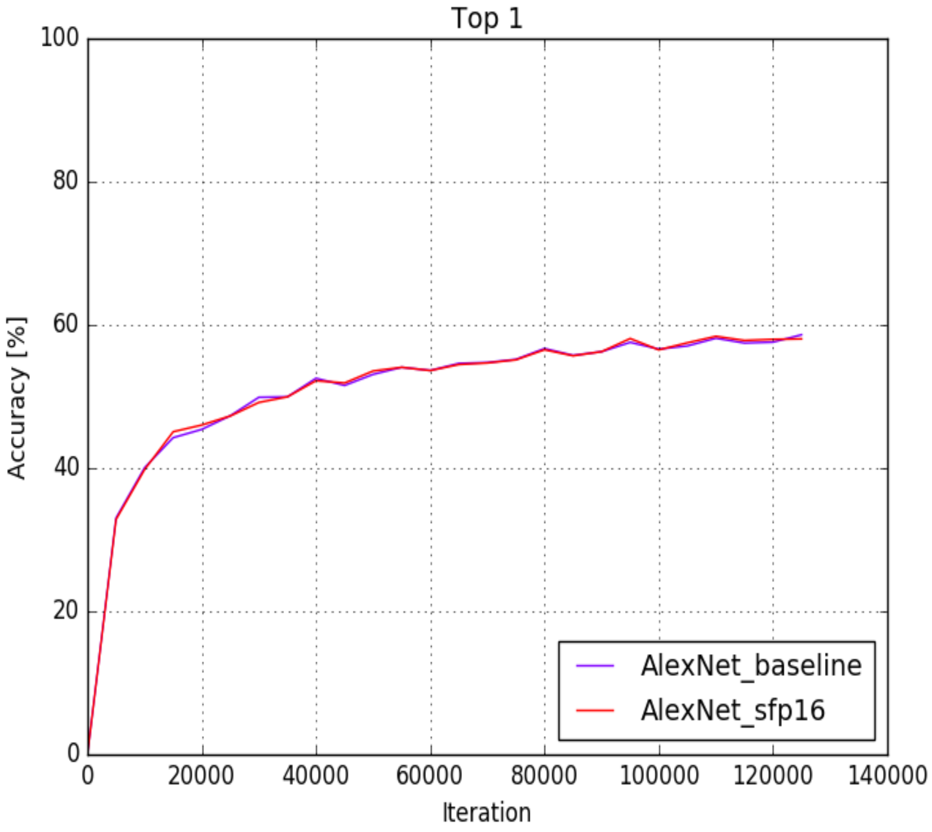
Update in float math: $W = half2float(W_{16}(t)) - \lambda*half2float(G_{16}(t+1))$

Convert result to float16: $W_{16}(t+1) = float2half(W)$

Do forward-backward with W_{16} ...

ALEXNET: FP16 MASTER WEIGHT STORAGE

With this fix we can have only one copy of weights in float16:



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FP16 training, loss scale = 1000	57.76	80.76
FP16 training, loss scale = 1000, FP16 master weight storage	58.56	80.89

Nvcaffe-0.16, DGX-1, SGD with momentum, 100 epochs, batch=1024, no augmentation, 1 crop, 1 model

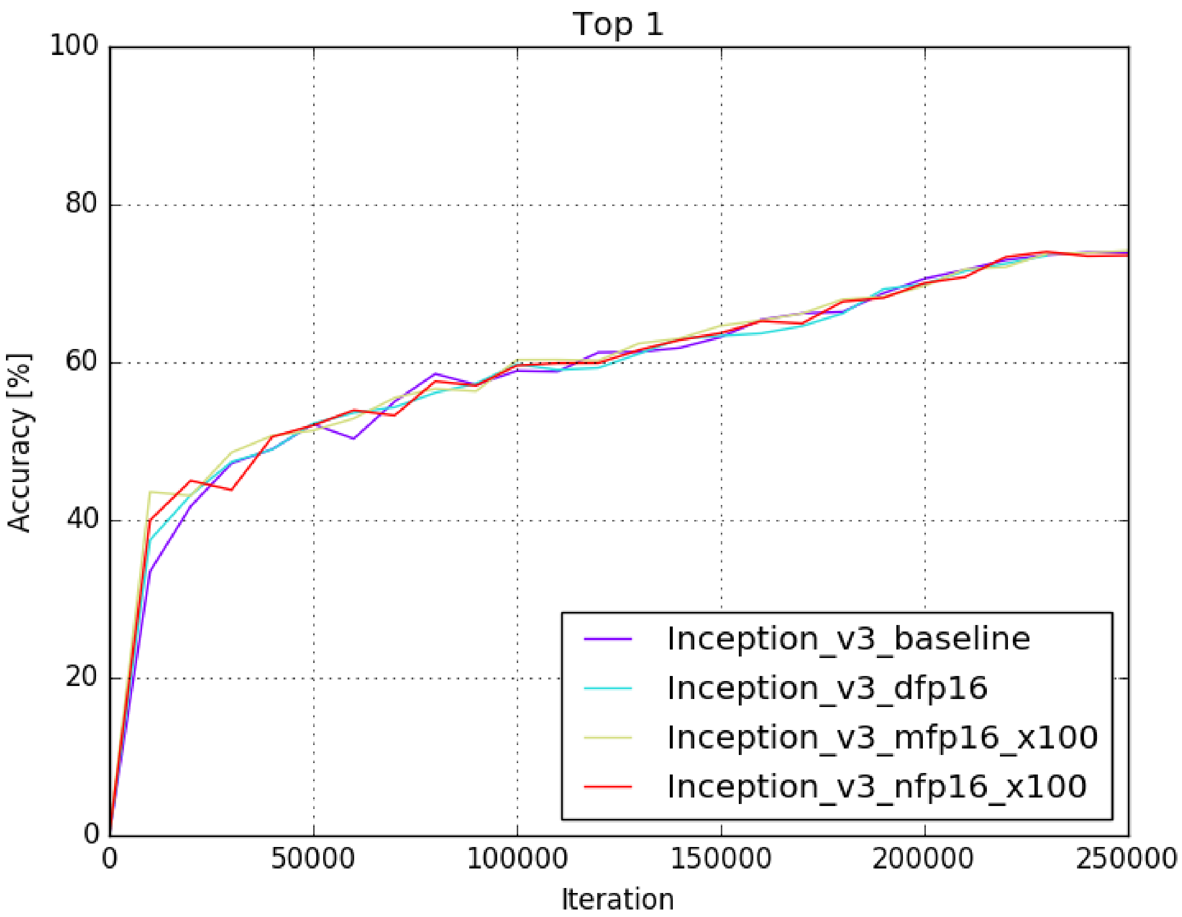
INCEPTION-V3 RESULTS

Scale loss function by 100x…

Mode	Top1 accuracy, %	Top5 accuracy, %
Fp32	73.85	91.44
Mixed precision training	73.6	91.11
FP16 training	71.36	90.84
FP16 training, loss scale = 100	74.13	91.51
FP16 training, loss scale = 100, FP16 master weight storage	73.52	91.08

Nvcaffe-0.16, DGX-1, SGD with momentum, 100 epochs, batch=512, no augmentation, 1 crop, 1 model

INCEPTION-V3 RESULTS



RESNET RESULTS

No scale of loss function ...

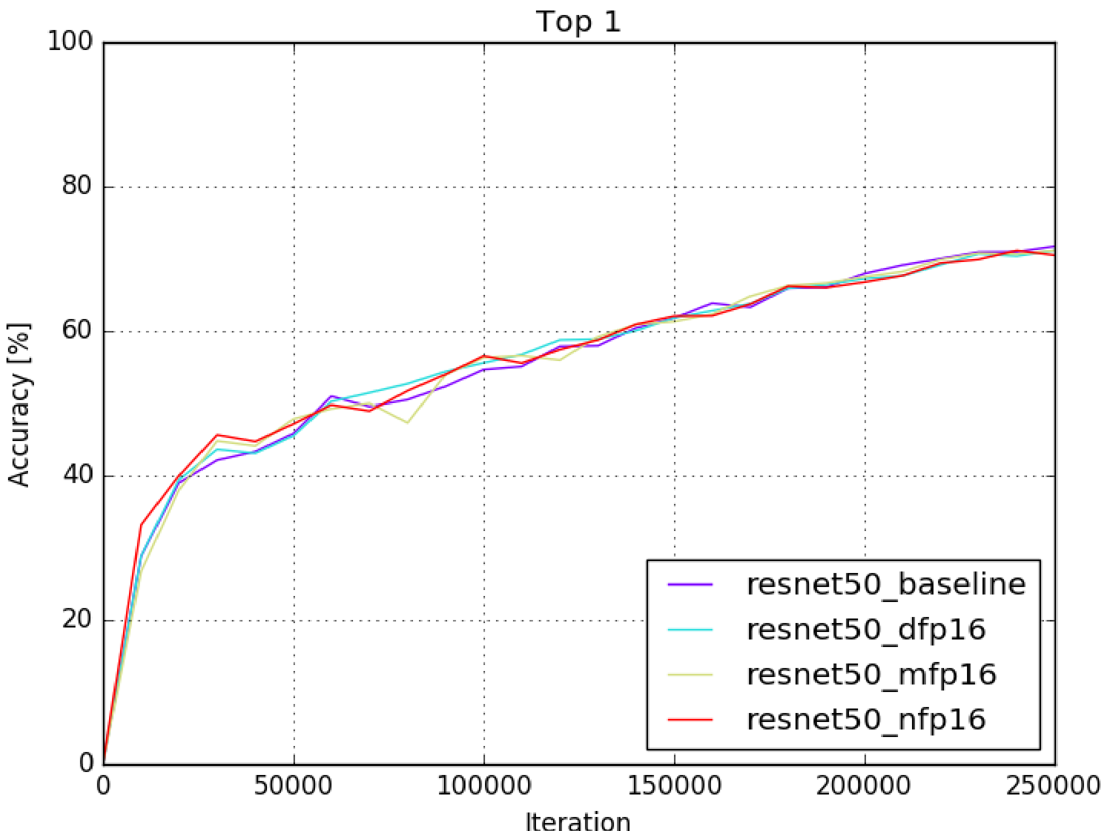
Mode	Top1 accuracy, %	Top5 accuracy, %
Fp32	71.75	90.52
Mixed precision training	71.17	90.10
FP16 training, loss scale = 1	71.17	90.33
FP16 training, loss scale = 1, FP16 master weight storage	70.53	90.14

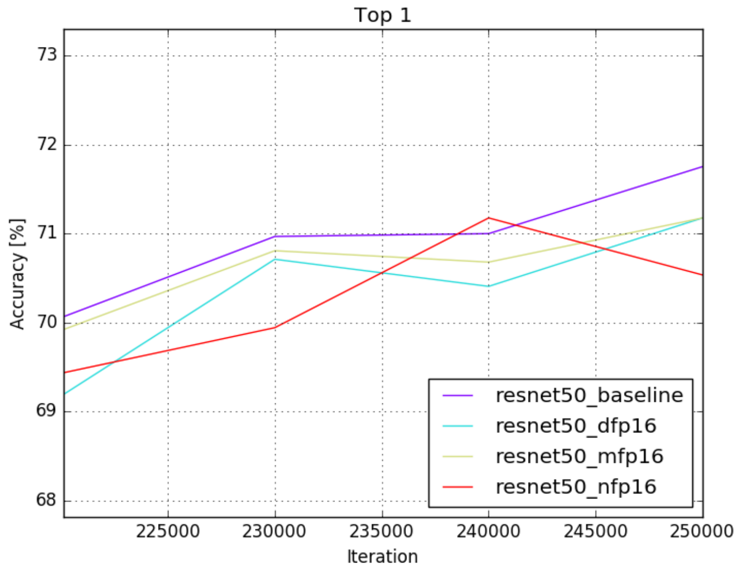
Nvcaffe-0.16, DGX-1, SGD with momentum, 100 epochs, batch=512, no augmentation, 1 crop, 1 model

RESNET-50 RESULTS

FP16 training is ok

FP16 storage has a small dip at the end (noise?)





OVERALL SUMMARY

1. Good results on **Volta mixed precision training** with a variety of networks
    - Applying a global scaling to the loss input is needed for some networks
    - Wide range of loss scaling values work well
2. **FP16 training** also works for a set of convnets using the loss scaling method – still exploratory
3. **FP16 master weight storage** also worked for a set of convnets after refactoring the solver – still exploratory
4. Overall current recommendation is "**mixed precision with FP32 master weight storage**" as the most robust training recipe

Part 3

Training with mixed precision in nvcaffe-0.16

NVIDIA/CAFFE-0.16

- Full float16 support
- Mixed precision:
  - Different *data types* for *Forward* and *Backward*
  - Different *math type*
  - *Solver_type (for* weight update in float16)
- Automatic type conversion
- Very fast!

https://github.com/NVIDIA/caffe/tree/caffe-0.16

NVIDIA/CAFFE-0.16

```
name: "AlexNet_fp16"

default_forward_type:  FLOAT16
default_backward_type: FLOAT16

default_forward_math:  FLOAT
default_backward_math: FLOAT

layer {
  forward_math:  FLOAT16
  backward_math: FLOAT
  …
}
```

```
solver_data_type: FLOAT16
```

https://github.com/NVIDIA/caffe/tree/caffe-0.16

NVIDIA/CAFFE-0.16 - INTERNALS

```
enum Type {
  DOUBLE = 0,
  FLOAT = 1,
  FLOAT16 = 2,
…
class Blob { …
  mutable shared_ptr<Tensor> data_tensor_;
  mutable shared_ptr<Tensor> diff_tensor_;
…
class Tensor { …
  Type type_;
  shared_ptr<vector<shared_ptr<SyncedMemory>>> synced_arrays_;
…
template<typename Dtype>
class TBlob : public Blob {
…
```

NVIDIA/CAFFE-0.16 - DATA AND MATH TYPES

```
default_forward_type:  FLOAT16
default_backward_type: FLOAT16
```

```
template<typename Ftype, typename Btype>
class Layer : public LayerBase {…
```

```
default_forward_math:  FLOAT
```

```
forward_math_ = this->layer_param().forward_math();
…
setConvolutionDesc(forward_math_, fwd_conv_descs_[i],
                   pad_h, pad_w, stride_h, stride_w);
```

NVIDIA/CAFFE-0.16 – SOLVER DATA TYPE

```
solver_data_type: FLOAT16
```

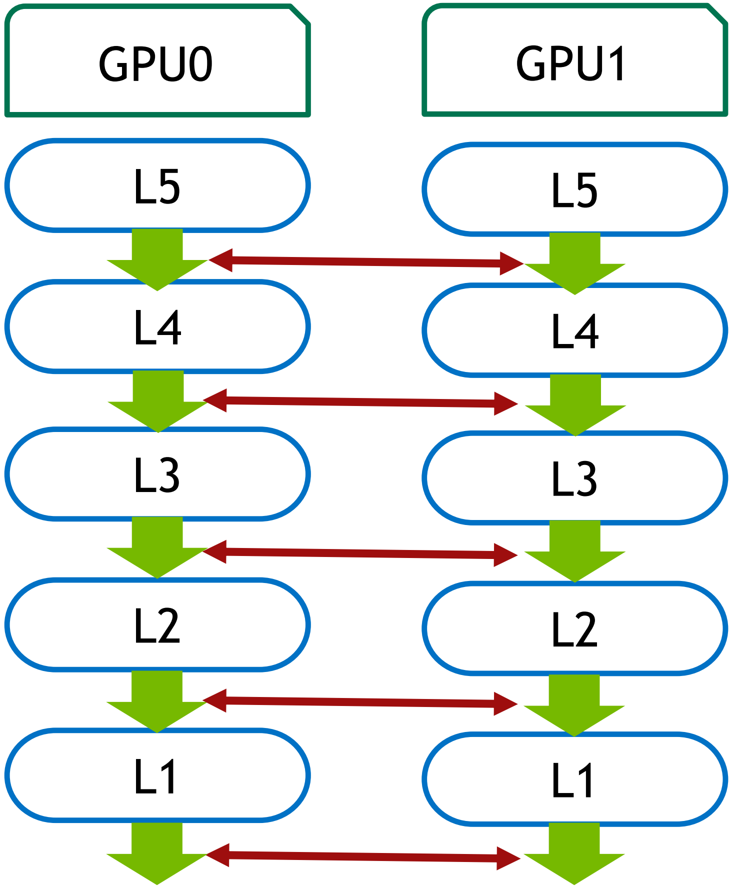
```
template <typename Dtype>
class SGDSolver : public Solver {
…
 vector<shared_ptr<TBlob<Dtype>>> history_, update_, temp_;
…


class Solver {
…
 shared_ptr<Net> net_;
 vector<shared_ptr<Net>> test_nets_;
…
```

NVIDIA/CAFFE-0.16 - FUSED KERNELS

```
template<typename Gtype, typename Wtype>
__global__ void SGDRegUpdateAllAndClear(int N, Gtype* g, Wtype* w, Wtype* h,
    float momentum, float local_rate, float local_decay, bool reg_L2, bool clear_grads) {
  CUDA_KERNEL_LOOP(i, N) {
    Wtype reg = reg_L2 ? w[i] : Wtype((Wtype(0) < w[i]) - (w[i] < Wtype(0)));
    Wtype gr = Wtype(g[i]) + reg * local_decay;
    gr = h[i] = momentum * h[i] + local_rate * gr;
    w[i] -= gr;
    g[i] = clear_grads ? Gtype(0) : Gtype(gr);
  }
}
template<> __global__ void SGDRegUpdateAllAndClear<__half, float>(int N,__half* g,float* w,
float* h, float momentum, float l_rate, float l_decay, bool reg_L2, bool clear_grads) {
  __half hz; hz.x = 0;
  CUDA_KERNEL_LOOP(i, N) {
    float reg = reg_L2 ? w[i] : (0.F < w[i]) - (w[i] < 0.F);
    float gr = __half2float(g[i]) + reg * l_decay;
    gr = h[i] = momentum * h[i] + l_rate * gr;
    w[i] -= gr;
    g[i] = clear_grads ? hz : float2half_clip(h[i]);
  }
}
```

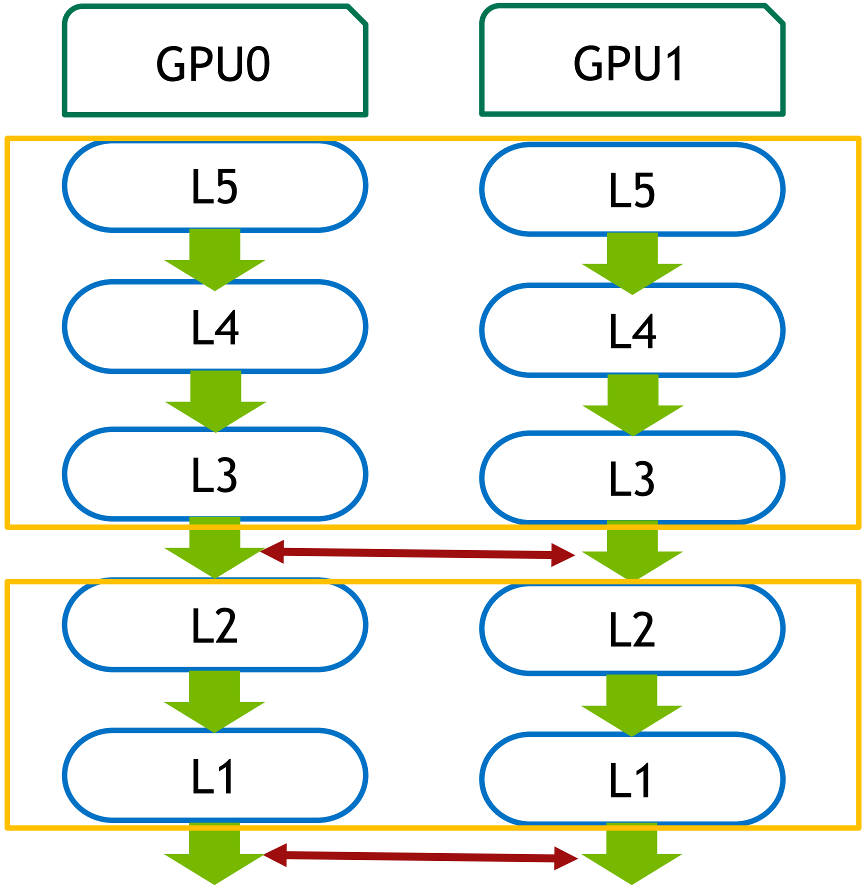
NVIDIA/CAFFE-0.16 – MULTIGPU REDUCTION




```
NCCL_CHECK(ncclAllReduce(send, receive, count,
     nccl::nccl_type(type), ncclSum, nccl_comm_,
     comm_stream_->get()));
```

- 1 call does it all
- FLOAT16 takes 2x less time
- Parallelize!
- After each layer or in the end of back propagation?

NVIDIA/CAFFE-0.16 – BUCKETS



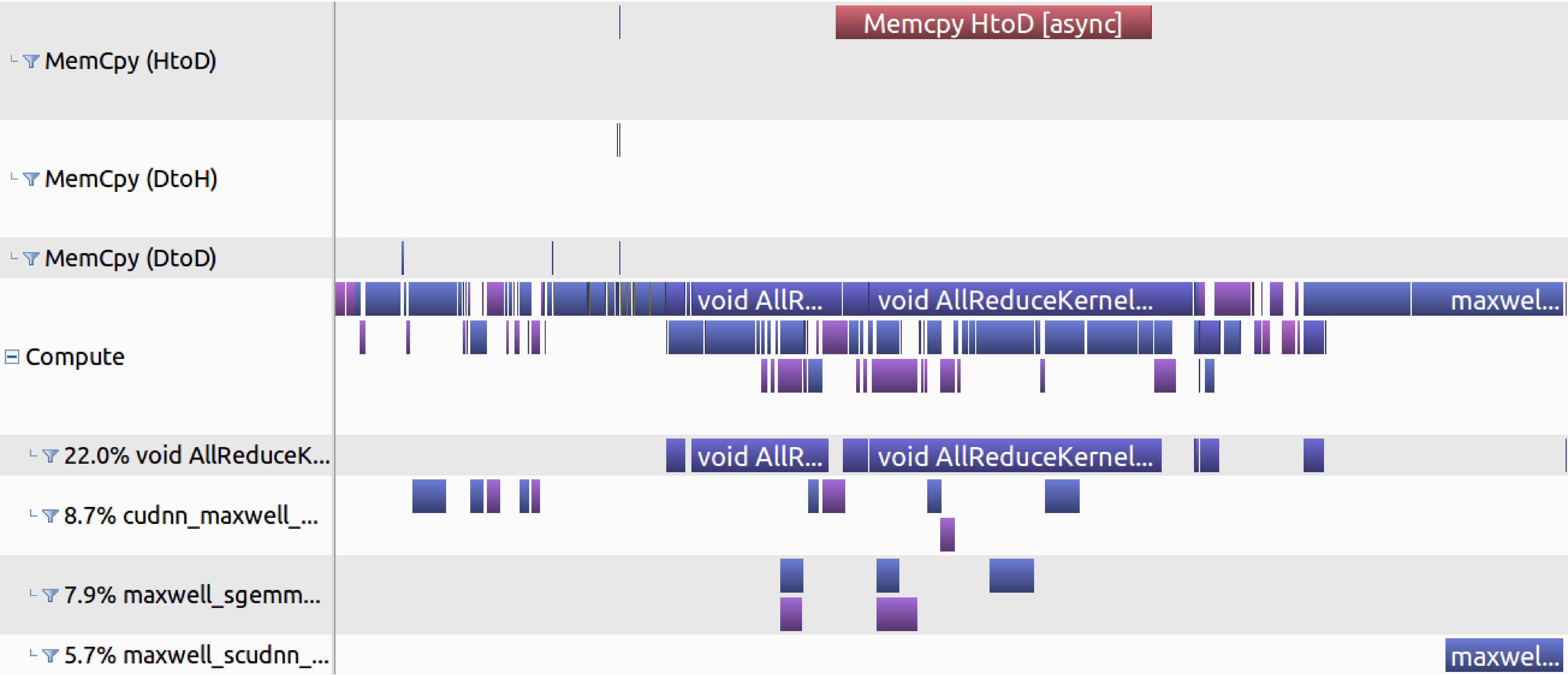
- 6-10 buckets per pass
- Weights Update + Reduce – one invocation per bucket
- Runs in a separate CUDA stream and gets synced in the end of back propagation pass

NVIDIA/CAFFE-0.16 – PARALLEL DATA READER

	Batch 0	Batch 1	Batch 2	Batch 3	Batch 4	Batch 5	Batch 6	Batch 7	TR	out queues
Solver 0 (GPU0)	S0.P0.q0						S0.P0.q3		→ →	S0.TR0.q0 S0.TR0.q1
		S0.P1.q1						S0.P1.q4	→ →	S0.TR0.q2 S0.TR1.q3
			S0.P2.q2						→ →	S0.TR1.q4 S0.TR1.q5
Solver 1 (GPU1)				S1.P0.q0					→ →	S1.TR0.q0 S1.TR0.q1
					S1.P1.q1				→ →	S1.TR0.q2 S1.TR1.q3
						S1.P2.q2			→ →	S1.TR1.q4 S1.TR1.q5

2 solvers, 3 parser threads per solver (P0, P1, P2), 2 transformer threads per solver (TR0, TR1) - each transformer owns queue set with the number of queues equal to the number of parser threads. 2x3x2=12 queues total. 2x3=6 DB cursors.

NVIDIA/CAFFE-0.16 – ALL TOGETHER NOW



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