GPU TECHNOLOGY CONFERENCE

Training Neural Networks with Mixed Precision

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PRESENTED BY NVIDIA.

THIS TALK

Using mixed precision and Volta your networks can be:

1. 2-4x faster
2. half the memory use
3. just as powerful

with no architecture change.

TALK OVERVIEW

1. Introduction to Mixed Precision Training
2. Mixed Precision Example in PyTorch
3. Appendix: Mixed Precision Example in TensorFlow

REFERENCES

(Further Reading)

- Paulius Micikevicius's talk "Training Neural Networks with Mixed Precision: Theory and Practice" (GTC 2018, S8923).
- "Mixed Precision Training" (ICLR 2018).
- "Mixed- Precision Training of Deep Neural Networks" (NVIDIA Parallel Forall Blog).
- "Training with Mixed Precision" (NVIDIA User Guide).

SINGLE VS HALF PRECISION

FP32	FP16 + Volta
1x compute throughput	8X compute throughput
1x memory throughput	2X memory throughput
1x size	1/2X size
32 bit precision	16 bit precision

MIXED PRECISION APPROACH

Imprecise weight updates	"Master" weights in FP32
Gradients may underflow	Loss (Gradient) Scaling
Maintain precision for reductions (sums, etc)	Accumulate in FP32

SUCCESS STORIES: SPEED

Pytorch

NVIDIA Sentiment Analysis: **4.5X** speedup*
FAIRSeq: **4X** speedup
GNMT: **2X** speedup

TensorFlow

Resnet152: **2.2X** speedup

*single Volta, Mixed Precision vs pure FP32

SUCCESS STORIES: ACCURACY

ILSVRC12 classification top-1 accuracy*

Model	FP32	Mixed Precision**
AlexNet	56.77%	56.93%
VGG-D	65.40%	65.43%
GoogLeNet (Inception v1)	68.33%	68.43%
Inception v2	70.03%	70.02%
Inception v3	73.85%	74.13%
Resnet50	75.92%	76.04%

*Sharan Narang, Paulius Micikevicius *et al.*, "Mixed Precision Training" (ICLR 2018)
**Same hyperparameters and learning rate schedule as FP32.

Mixed precision can match FP32 with no change in hyperparameters.

SUCCESS STORIES: ACCURACY

Progressive Growing of GANs: Generates 1024x1024 face images

http://research.nvidia.com/publication/2017-10_Progressive-Growing-of

No perceptible difference between FP32 and mixed-precision training

Loss-scaling:

Separate scaling factors for generator and discriminator (you are training 2 networks)

Automatic loss scaling greatly simplified training – gradient stats shift drastically when image resolution is increased

THIS TALK (REPRISE)

Using mixed precision and Volta your networks can be:

1. 2-4x faster
2. half the memory use
3. just as powerful

with no architecture change.

TENSOR CORE PERFORMANCE TIPS

- Convolutions:
  Batch size, input channels, output channels should be multiples of 8.
- GEMM:
  For A x B where A has size (N, M) and B has size (M, K), N, M, K should be multiples of 8.
- Fully connected layers are GEMMs:
  Batch size, input features, output features should be multiples of 8.

Libraries (cuDNN, cuBLAS) are optimized for Tensor Cores.

TENSOR CORE PERFORMANCE TIPS

How can I make sure Tensor Cores were used?
Run one iteration with nvprof, and look for “884” kernels:

```
import torch
import torch.nn

bsz, in, out = 256, 1024, 2048

tensor = torch.randn(bsz, in).cuda().half()
layer = torch.nn.Linear(in, out).cuda().half()
layer(tensor)
```

Running with

```
$ nvprof python test.py
...
37.024us  1  37.024us  37.024us  37.024us  volta_fp16_s884gemm_fp16…
```

TENSOR CORE PERFORMANCE TIPS

If your data/layer sizes are constant each iteration, try

```
import torch
torch.backends.cudnn.benchmark = True
...
```

This enables cuDNN's autotuner. The first iteration, it will try many algorithms, and choose the fastest to use in later iterations.

See https://discuss.pytorch.org/t/what-does-torch-backends-cudnn-benchmark-do/5936

PYTORCH EXAMPLE

A SIMPLE NETWORK

```
N, D_in, D_out = 64, 1024, 512

x = Variable(torch.randn(N, D_in )).cuda()
y = Variable(torch.randn(N, D_out)).cuda()

model = torch.nn.Linear(D_in, D_out).cuda()

optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

CONVERT TO FP16

This may be all you need to do!

```
N, D_in, D_out = 64, 1024, 512

x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()

model = torch.nn.Linear(D_in, D_out).cuda().half()

optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

CONVERT TO FP16

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N, D_in, D_out = 64, 1024, 512

x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()

model = torch.nn.Linear(D_in, D_out).cuda().half()

optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

This may be all you need to do!

Sometimes you need to use mixed precision.

MIXED PRECISION APPROACH

Imprecise weight updates → "Master" weights in FP32

Gradients may underflow → Loss (Gradient) Scaling

Maintain precision for reductions (sums, etc) → Accumulate in FP32

IMPRECISE WEIGHT UPDATES

$$1 + 0.0001 = ?$$

FP32:

```
param = torch.cuda.FloatTensor([1.0])
print(param + 0.0001)
```

→ 1.0001

FP16:

```
param = torch.cuda.HalfTensor([1.0])
print(param + 0.0001)
```

→ 1

When *update/param* < 2^{-11}, updates have no effect.

IMPRECISE WEIGHT UPDATES

```
N, D_in, D_out = 64, 1024, 512

x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()

model = torch.nn.Linear(D_in, D_out).cuda().half()

optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)

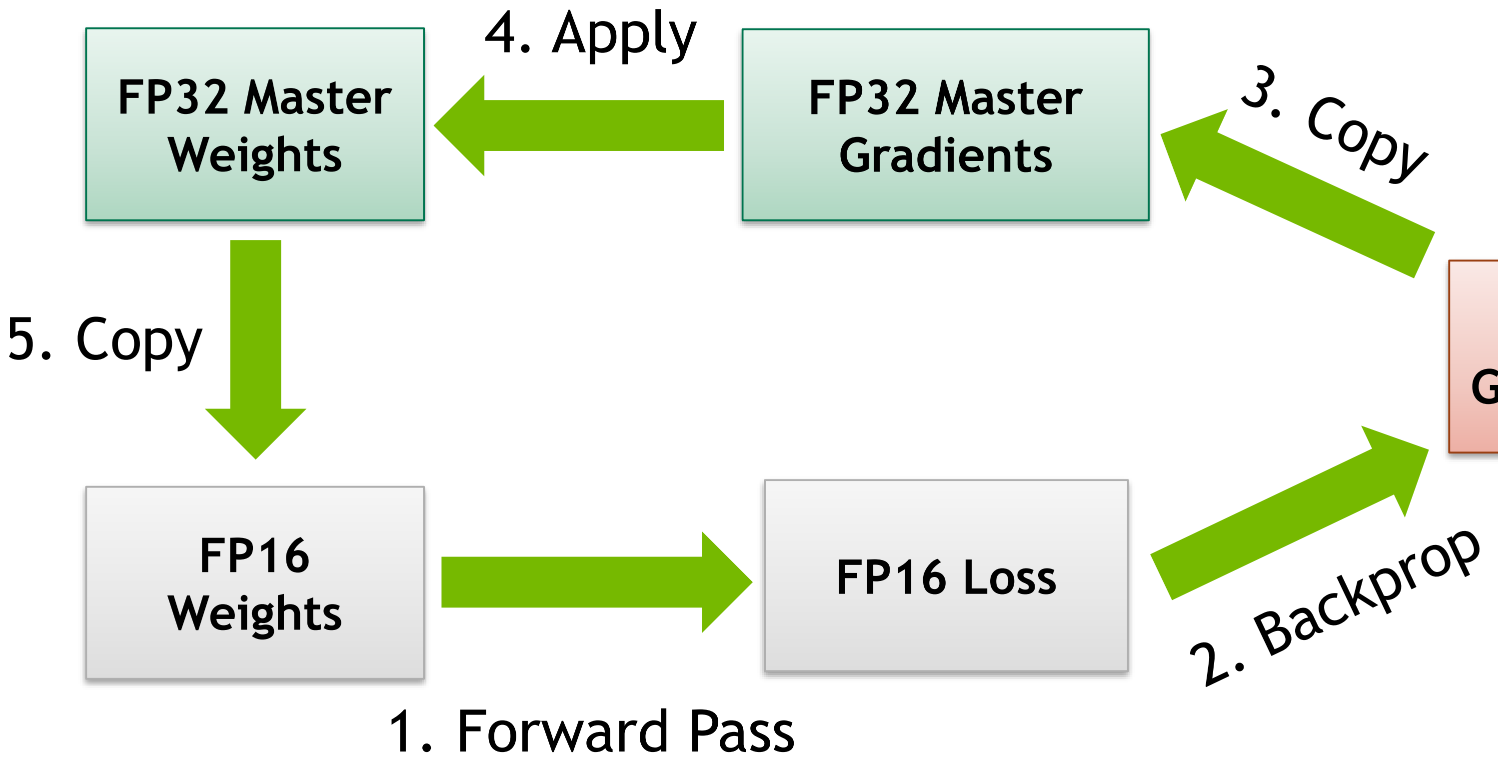
for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred, y)

    optimizer.zero_grad()
    loss.backward()
    optimizer.step()
```

Small FP16 weight updates may be lost

MIXED SOLUTION: FP32 MASTER WEIGHTS



MIXED SOLUTION: FP32 MASTER WEIGHTS

Helper Functions

```python
def prep_param_lists(model):
    model_params  = [p for p in model.parameters()
                                if p.requires_grad]
    master_params = [p.clone().detach().float()
                               for p in model_params]

    for p in master_params:
        p.requires_grad = True

    return model_params, master_params
```

FP32 Master Weights

Note: Model<->master param and gradient copies act on `.data` members.
They are not recorded by Pytorch's autograd system.

MIXED SOLUTION: FP32 MASTER WEIGHTS

```
N, D_in, D_out = 64, 1024, 512

x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()

model = torch.nn.Linear(D_in, D_out).cuda().half()
model_params, master_params = prep_param_lists(model)

optimizer = torch.optim.SGD(master_params, lr=1e-3)
```

Optimizer updates FP32 master params

```
for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred, y)

    model.zero_grad()
    loss.backward()
    optimizer.step()
```

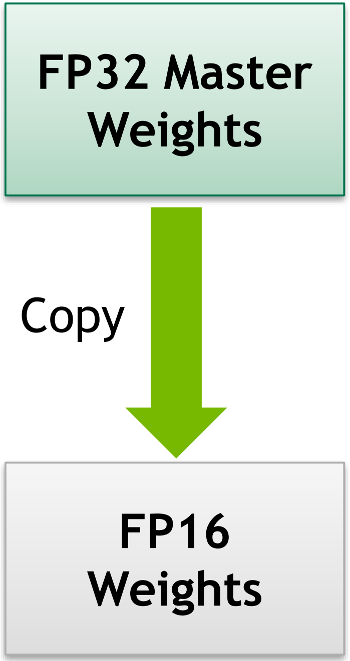
Zero FP16 grads by calling model.zero_grad() instead of optimizer.zero_grad()

FP32 Master Weights

MIXED SOLUTION: FP32 MASTER WEIGHTS

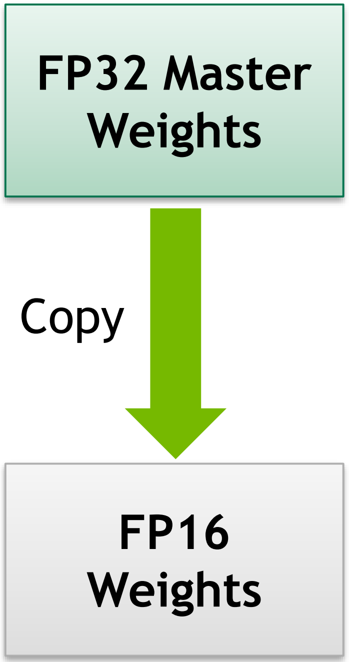
Helper Functions

```
def master_params_to_model_params(model_params, master_params):
    for model, master in zip(model_params, master_params):
        model.data.copy_(master.data)
```



MIXED SOLUTION: FP32 MASTER WEIGHTS

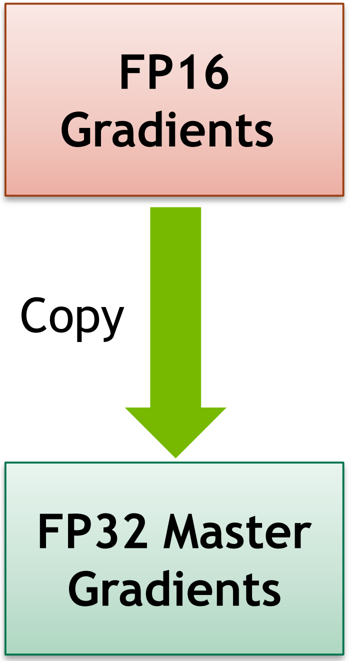
```
N, D_in, D_out = 64, 1024, 512
x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()
model = torch.nn.Linear(D_in, D_out).cuda().half()
model_params, master_params = prep_param_lists(model)

optimizer = torch.optim.SGD(master_params, lr=1e-3)

for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    model.zero_grad()
    loss.backward()
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```



MIXED SOLUTION: FP32 MASTER WEIGHTS

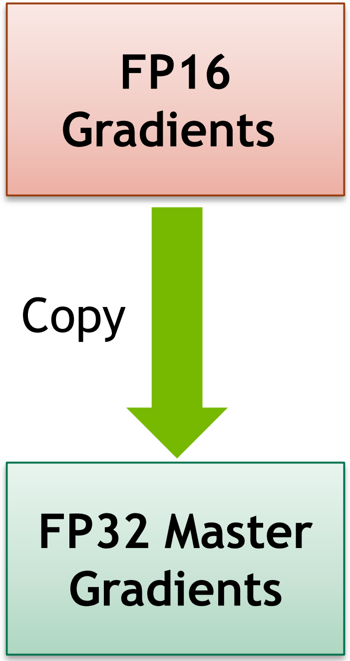
Helper Functions

```python
def model_grads_to_master_grads(model_params, master_params):
    for model, master in zip(model_params, master_params):
        if master.grad is None:
            master.grad = Variable(
              master.data.new(*master.data.size()))
        master.grad.data.copy_(model.grad.data)
```

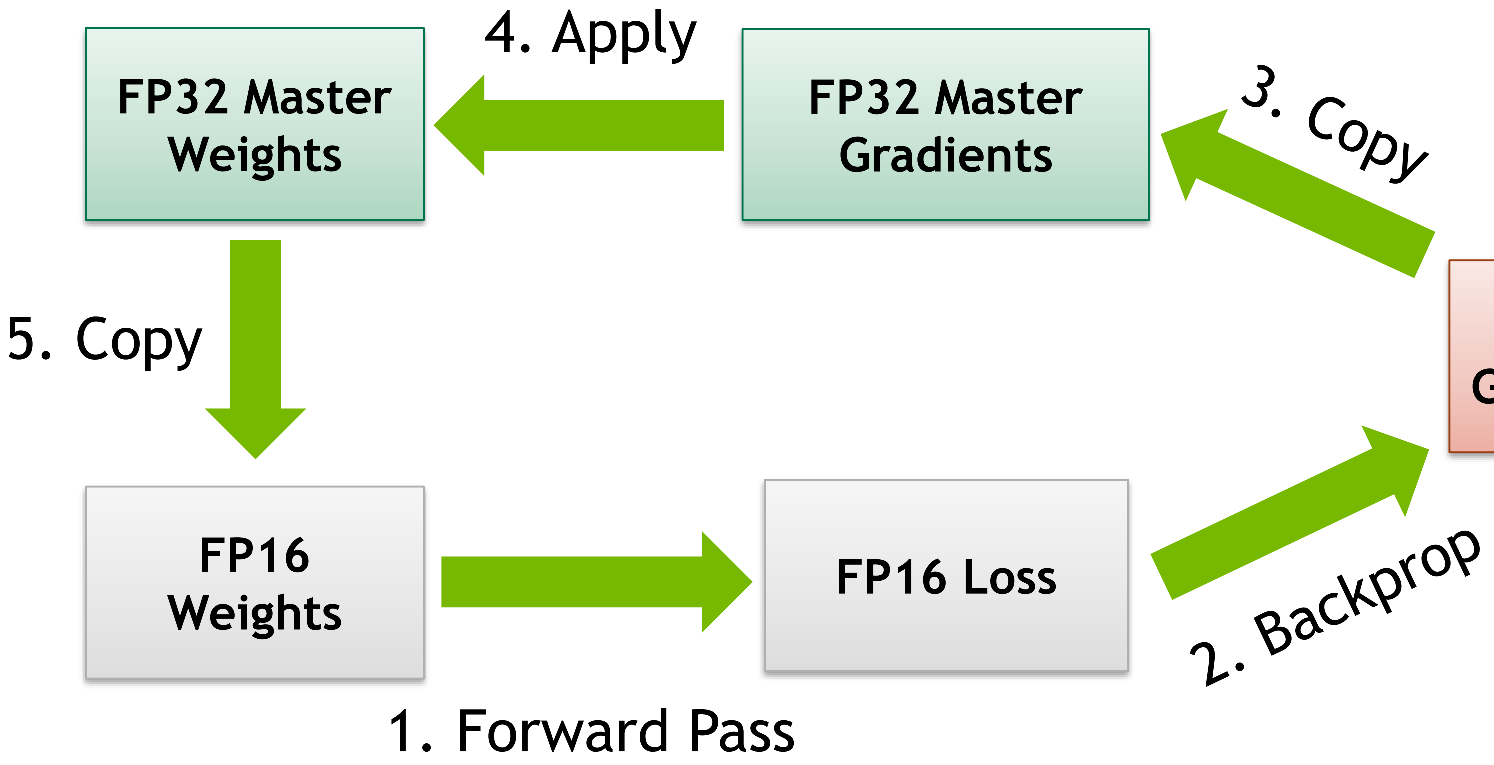


MIXED SOLUTION: FP32 MASTER WEIGHTS

```
N, D_in, D_out = 64, 1024, 512
x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()
model = torch.nn.Linear(D_in, D_out).cuda().half()
model_params, master_params = prep_param_lists(model)

optimizer = torch.optim.SGD(master_params, lr=1e-3)

for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    model.zero_grad()
    loss.backward()
    model_grads_to_master_grads(model_params, master_params)
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```



MIXED SOLUTION: FP32 MASTER WEIGHTS

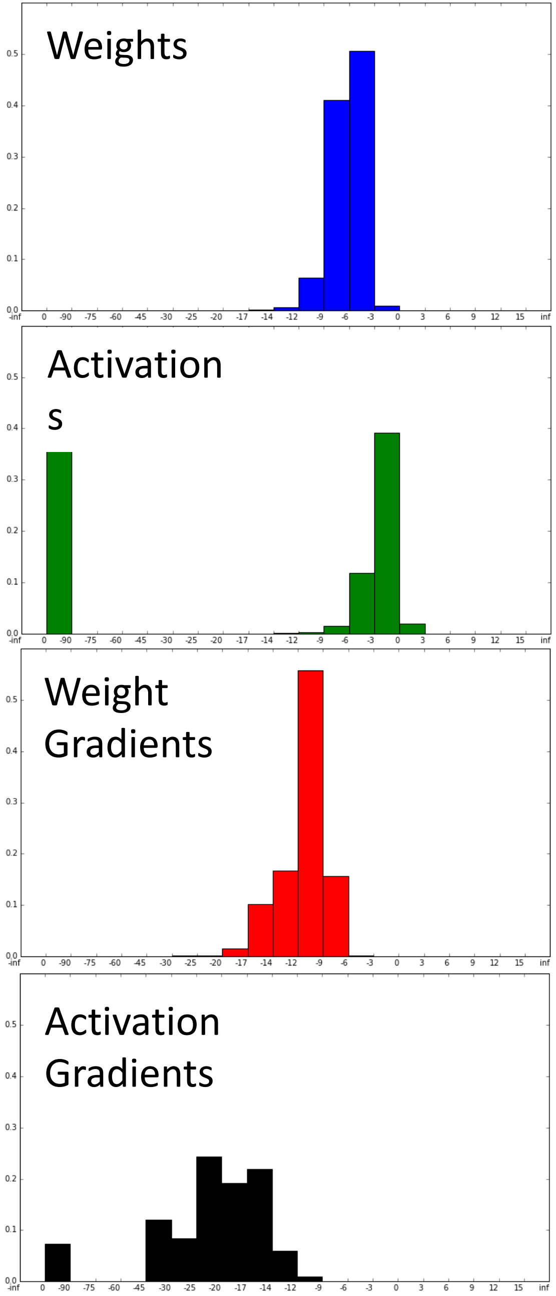


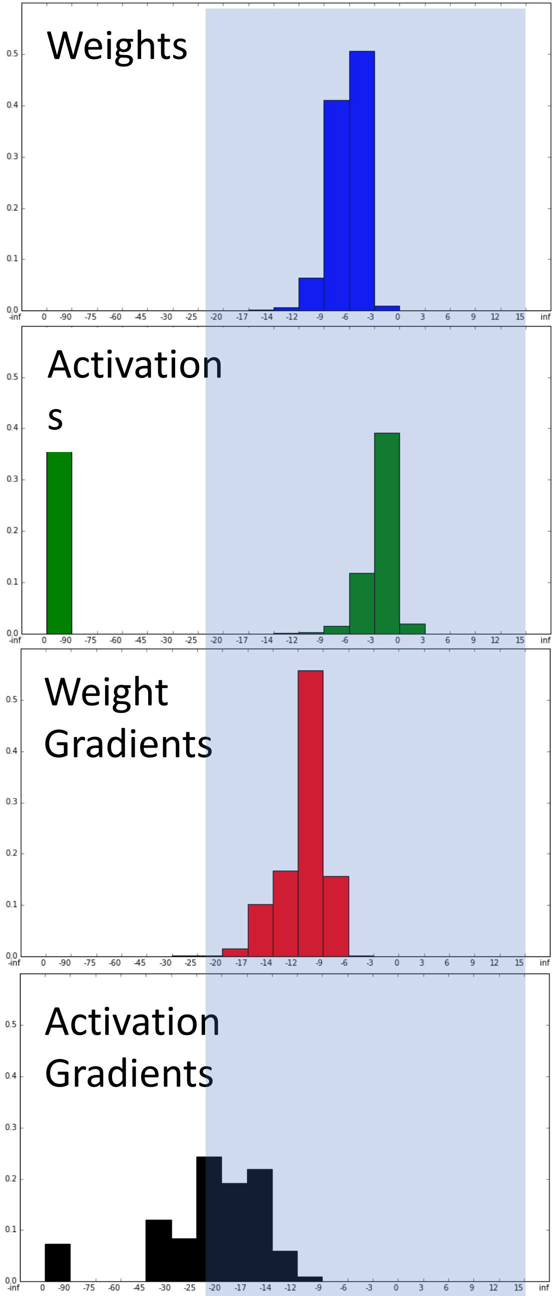
MIXED PRECISION APPROACH

Imprecise weight updates	→	"Master" weights in FP32 ✓
Gradients may underflow	→	Loss (Gradient) Scaling
Maintain precision for reductions (sums, etc)	→	Accumulate in FP32

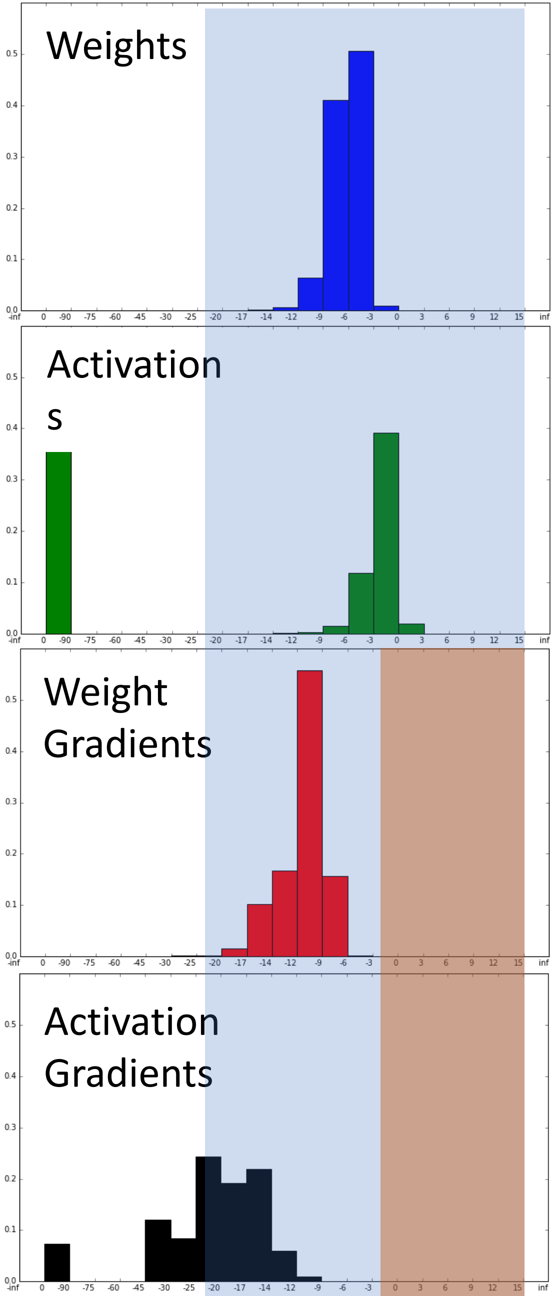
GRADIENTS MAY UNDERFLOW

```
N, D_in, D_out = 64, 1024, 512
x = Variable(torch.randn(N, D_in )).cuda().half()
y = Variable(torch.randn(N, D_out)).cuda().half()
model = torch.nn.Linear(D_in, D_out).cuda().half()
model_params, master_params = prep_param_lists(model)

optimizer = torch.optim.SGD(master_params, lr=1e-3)

for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    model.zero_grad()
    loss.backward()
    model_grads_to_master_grads(model_params, master_params)
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```


Weights
Activation
s
Weight
Gradients
Activation
Gradients



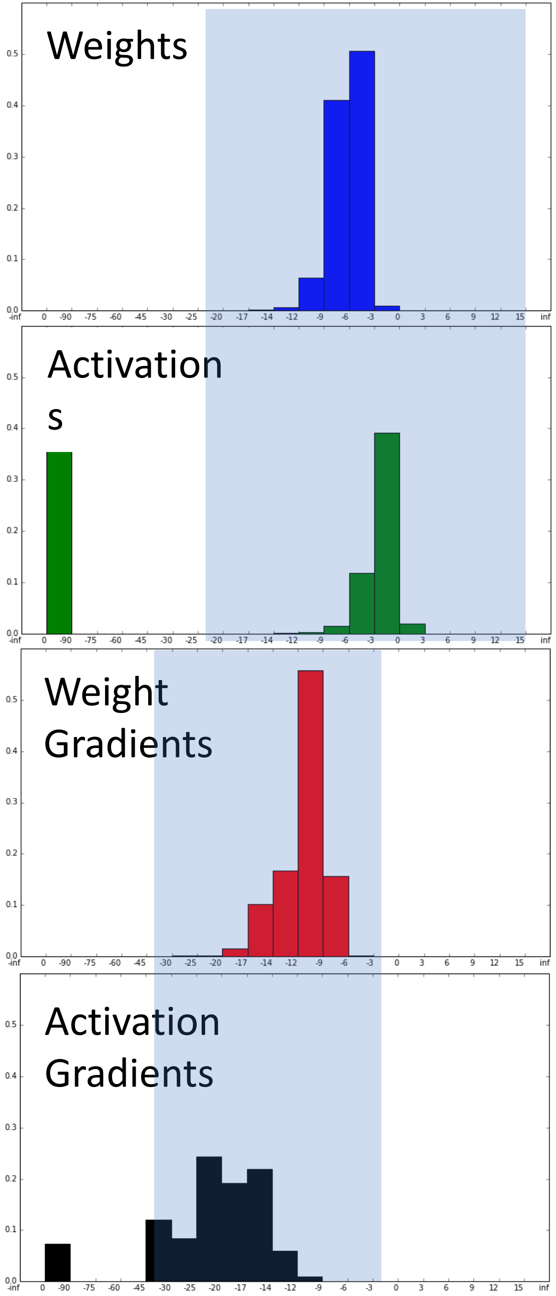
Range representable in FP16: ~40 powers of 2



Range representable in FP16: ~40 powers of 2

Gradients are small, don’t use much of FP16 range

FP16 range not used by gradients: ~15 powers of 2



Range representable in FP16: ~40 powers of 2

Gradients are small, don’t use much of FP16 range

FP16 range not used by gradients: ~15 powers of 2

Loss Scaling

1. Multiply the loss by some constant **S**.
2. Call **`backward()`** on scaled loss.
   By chain rule, gradients will also be scaled by **S**.
   This preserves small gradient values.
3. Unscale gradients before update **`step()`**.

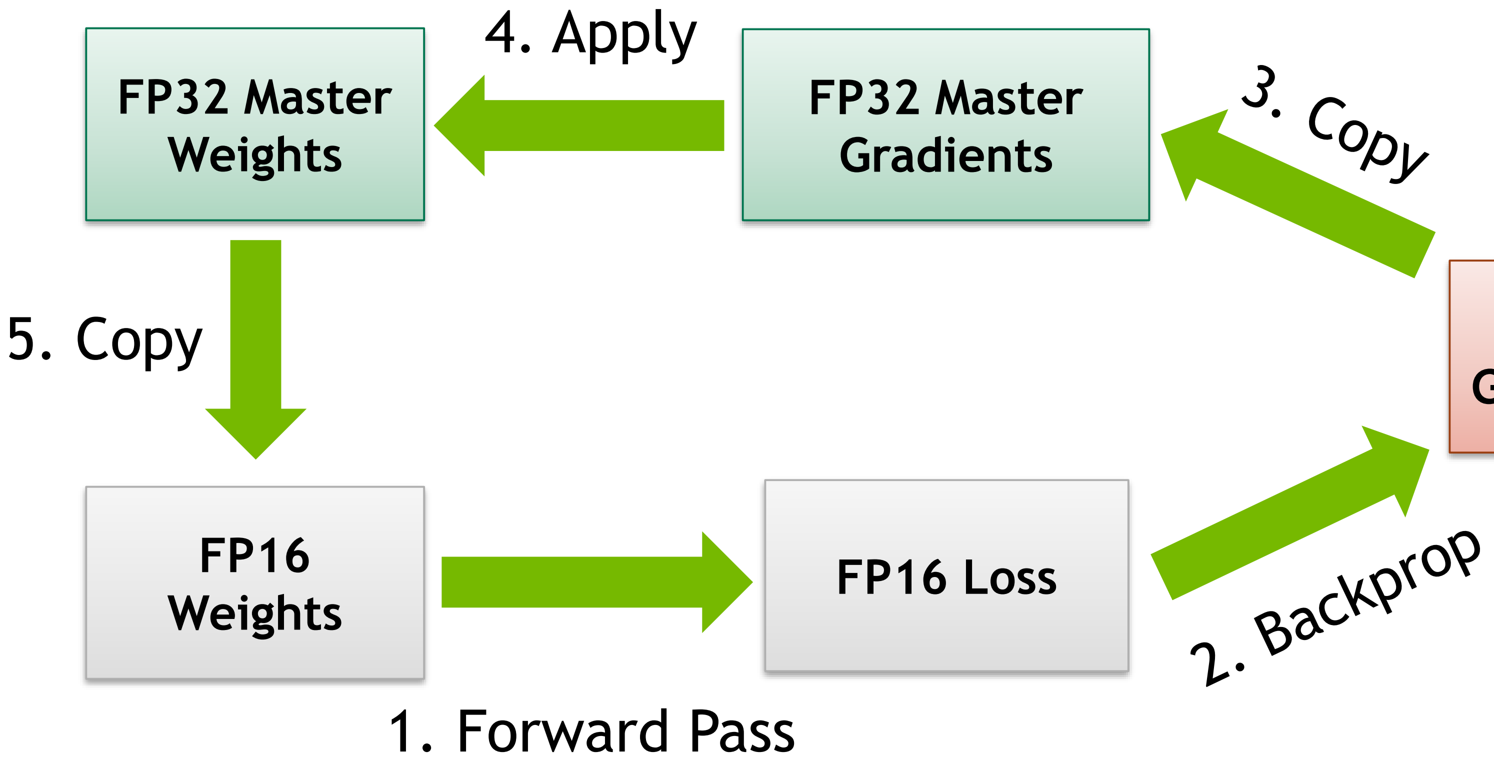
MIXED SOLUTION: LOSS (GRADIENT) SCALING

```
N, D_in, D_out = 64, 1024, 512
scale_factor = 128.0

......

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred,y)
    scaled_loss = scale_factor * loss.float()

    model.zero_grad()
    scaled_loss.backward()
    model_grads_to_master_grads(model_params, master_params)

    for param in master_params:
        param.grad.data.mul_(1./scale_factor)
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```

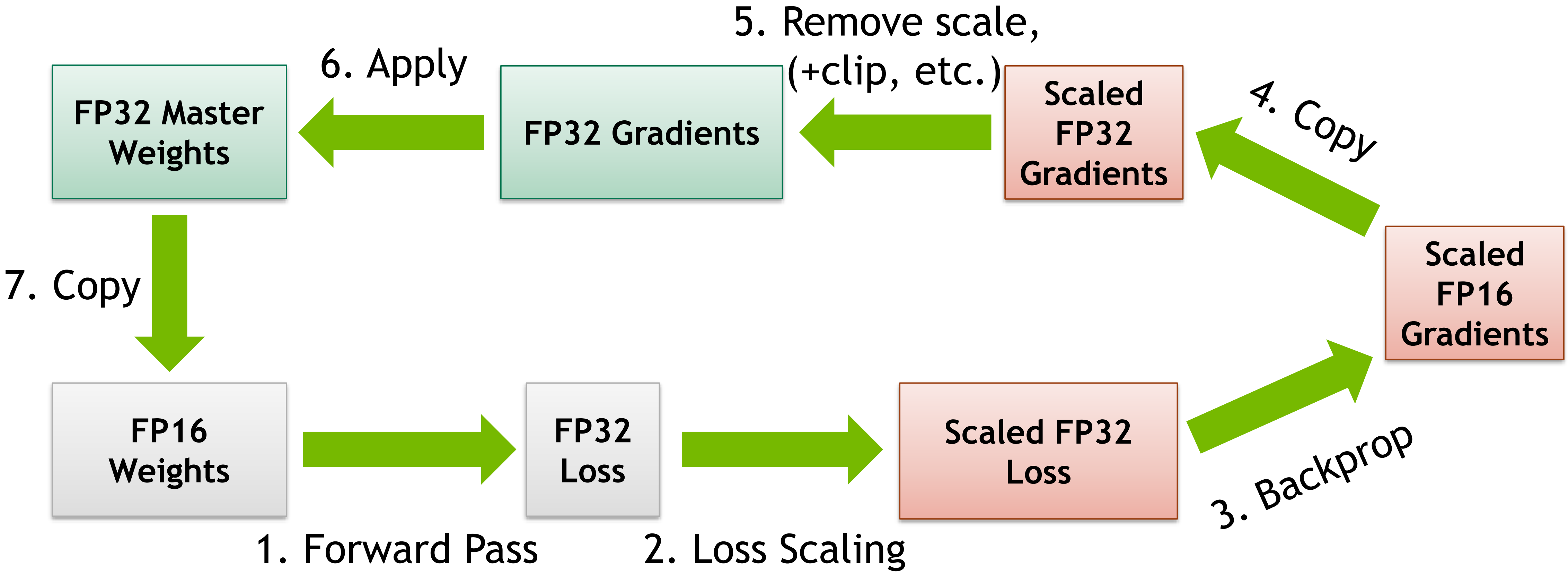
Gradients are now rescaled to be representable

The FP32 master gradients must be "descaled"

MASTER WEIGHTS



MASTER WEIGHTS + LOSS SCALING



LOSS SCALING FAQ

1. Does loss scaling require retuning the learning rate?

   No. Loss scaling is orthogonal to learning rate. Changing loss scale should not require retuning other hyperparameters.

2. Can the loss scale be adjusted each iteration?

   Yes. For example, use larger loss scale later in training, when gradients are smaller.

   Dynamic loss scaling adjusts loss scale automatically (more on that later)

MIXED PRECISION APPROACH

Imprecise weight updates	→	"Master" weights in FP32 ✓
Gradients may underflow	→	Loss (Gradient) Scaling ✓
Maintain precision for reductions (sums, etc)	→	Accumulate in FP32

REDUCTIONS MAY OVERFLOW

In PyTorch 0.5:

```
a = torch.cuda.HalfTensor(4094).fill_(16.0)
a.sum()
```

65,504

```
b = torch.cuda.HalfTensor(4095).fill_(16.0)
b.sum()
```

inf

Reductions like `sum()` can overflow if > 65,504 is encountered.

Behavior may depend on Pytorch version.

REDUCTIONS MAY OVERFLOW

```
N, D_in, D_out = 64, 1024, 512
scale_factor = 128.0

......

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred,y)
    scaled_loss = scale_factor * loss.float()

    model.zero_grad()
    scaled_loss.backward()
    model_grads_to_master_grads(model_params, master_params)

    for param in master.params:
        param.grad.data.mul_(1./scale_factor)
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```

mse_loss is a reduction

MIXED SOLUTION: ACCUMULATE IN FP32

```
N, D_in, D_out = 64, 1024, 512
scale_factor = 128.0

......

for t in range(500):
    y_pred = model(x)

    loss = torch.nn.functional.mse_loss(y_pred.float(),y.float())
    scaled_loss = scale_factor * loss

    model.zero_grad()
    scaled_loss.backward()
    model_grads_to_master_grads(model_params, master_params)

    for param in master.params:
        param.grad.data.mul_(1./scale_factor)
    optimizer.step()
    master_params_to_model_params(model_params, master_params)
```

loss is now FP32
(Model grads are still FP16)

OTHER REDUCTIONS

BatchNorm involves a reduction.
BatchNorm may also need to be done in FP32:

```
def BN_convert_float(module):
    if isinstance(module, torch.nn.modules.batchnorm._BatchNorm):
        module.float()
    for child in module.children():
        BN_convert_float(child)
    return module
```

MIXED PRECISION APPROACH

Imprecise weight updates	"Master" weights in FP32 ✓
Gradients may underflow	Loss (Gradient) Scaling ✓
Maintain precision for reductions (sums, etc)	Accumulate in FP32 ✓

ADDITIONAL CONSIDERATIONS

Checkpointing

1. Save master weights.
2. Save gradient scale factor.

ADDITIONAL CONSIDERATIONS

Dynamic loss scaling

Prevent gradient UNDERflow by using the highest loss scale that does not cause gradient OVERflow.

1. Start with a large loss scale (e.g. 2^32)
2. After each iteration, check if gradients overflowed (NaN or +/- Inf).
3. If gradients overflowed, discard that iteration by skipping optimizer.step().
4. If gradients overflowed, reduce S for the next iteration (e.g. S = S/2)
5. If N (e.g. 1000) iterations pass with no overflow, increase S again (S = S*2).

More detail:
https://nvidia.github.io/apex/fp16_utils.html#apex.fp16_utils.DynamicLossScaler
Example:
https://github.com/NVIDIA/apex/blob/ea93767d22818bdd88ae738a8c7cf62b49a8fdaf/apex/fp16_utils/loss_scaler.py#L134-L186

NVIDIA MIXED PRECISION TOOLS

APEX - A PyTorch Extension

- All utility functions in this talk (`model_grads_to_master_grads`, etc.)
- `FP16_Optimizer`: Optimizer wrapper that automatically manages loss scaling + master params
    - Closure-safe
    - Option to automatically manage dynamic loss scaling
    - Compatible with Pytorch distributed training

www.github.com/nvidia/apex

Documentation: https://nvidia.github.io/apex/fp16_utils.html

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#GTC18

TENSORFLOW EXAMPLE

TENSORFLOW MIXED PRECISION SUPPORT

TensorFlow supports mixed precision using tf.float32 and tf.float16 data types

Reduce memory and bandwidth by using float16 tensors

Improve compute performance by using float16 matmuls and convolutions

Maintain training accuracy by using mixed precision

MIXED PRECISION TRAINING CONVERSION STEPS

1. Convert model to float16 data type
2. Use float32 for certain ops to avoid overflow or underflow
   - Reductions (e.g., norm, softmax)
   - Range-expanding math functions (e.g., exp, pow)
3. Use float32 for weights storage to avoid imprecise training updates
4. Apply loss scaling to avoid gradients underflow

EXAMPLE (PART 1)

Simple CNN model

```python
import tensorflow as tf
import numpy as np

def build_forward_model(inputs):
    _, _, h, w = inputs.get_shape().as_list()
    top_layer = inputs
    top_layer = tf.layers.conv2d(top_layer, 64, 7, use_bias=False,
                                 data_format='channels_first', padding='SAME')
    top_layer = tf.contrib.layers.batch_norm(top_layer, data_format='NCHW', fused=True)
    top_layer = tf.layers.max_pooling2d(top_layer, 2, 2, data_format='channels_first')
    top_layer = tf.reshape(top_layer, (-1, 64 * (h // 2) * (w // 2)))
    top_layer = tf.layers.dense(top_layer, 128, activation=tf.nn.relu)
    return top_layer
```

EXAMPLE (PART 1)

Simple CNN model

```
import tensorflow as tf
import numpy as np

def build_forward_model(inputs):
    _, _, h, w = inputs.get_shape().as_list()
    top_layer = inputs
    top_layer = tf.layers.conv2d(top_layer, 64, 7, use_bias=False,
                                 data_format='channels_first', padding='SAME')
    top_layer = tf.contrib.layers.batch_norm(top_layer, data_format='NCHW', fused=True)
    top_layer = tf.layers.max_pooling2d(top_layer, 2, 2, data_format='channels_first')
    top_layer = tf.reshape(top_layer, (-1, 64 * (h // 2) * (w // 2)))
    top_layer = tf.layers.dense(top_layer, 128, activation=tf.nn.relu)
    return top_layer
```

Convolutions support Tensor Cores

Batchnorm supports mixed precision

Matrix multiplications support Tensor Cores

Majority of TF ops support float16 data type

EXAMPLE (PART 2)

(We'll come back to this)

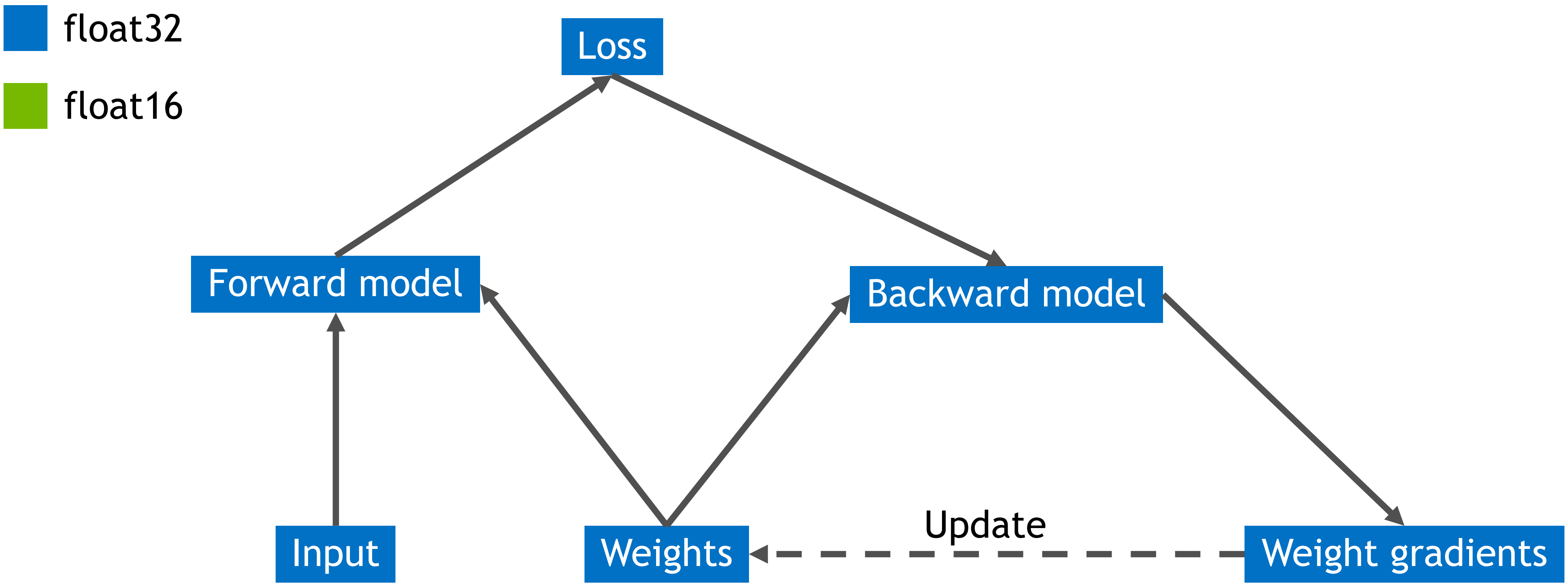
```
def build_training_model(inputs, labels, nlabel):
    top_layer = build_forward_model(inputs)
    logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```

EXAMPLE (PART 3)

Training boilerplate

```
nchan, height, width, nlabel = 3, 224, 224, 1000
inputs = tf.placeholder(tf.float32, (None, nchan, height, width))
labels = tf.placeholder(tf.int32,   (None,))
inputs, labels, loss, train_op = build_training_model(inputs, labels, nlabel)
batch_size = 128
sess = tf.Session()
inputs_np = np.random.random(size=(batch_size, nchan, height, width)).astype(np.float32)
labels_np = np.random.randint(nlabel, size=(batch_size,)).astype(np.int32)
sess.run(tf.global_variables_initializer())
for step in range(20):
    loss_np, _ = sess.run([loss, train_op],
                          {inputs: inputs_np,
                           labels: labels_np})
    print("Loss =", loss_np)
```

ORIGINAL GRAPH



STEP 1: CONVERSION TO FP16

```
def build_training_model(inputs, labels, nlabel):
    top_layer = build_forward_model(inputs)
    logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```

STEP 1: CONVERSION TO FP16

```
def build_training_model(inputs, labels, nlabel):
    inputs    = tf.cast(inputs, tf.float16)
    top_layer = build_forward_model(inputs)
    logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
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    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```
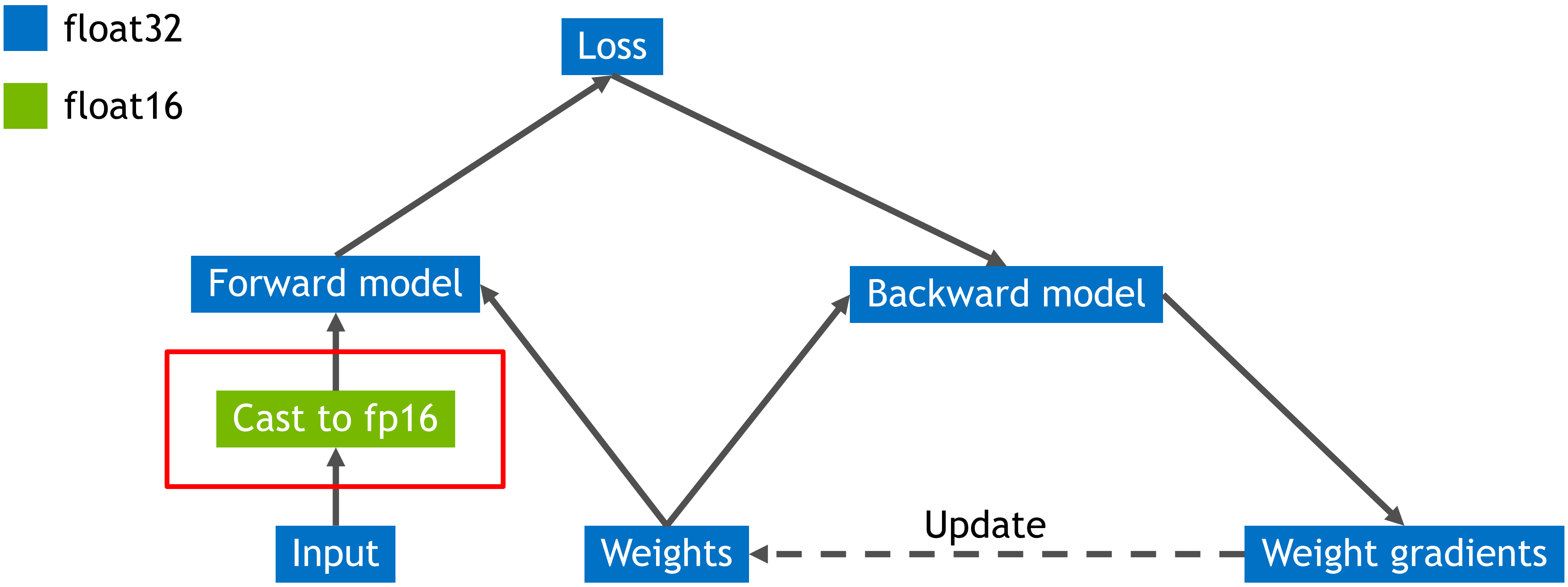
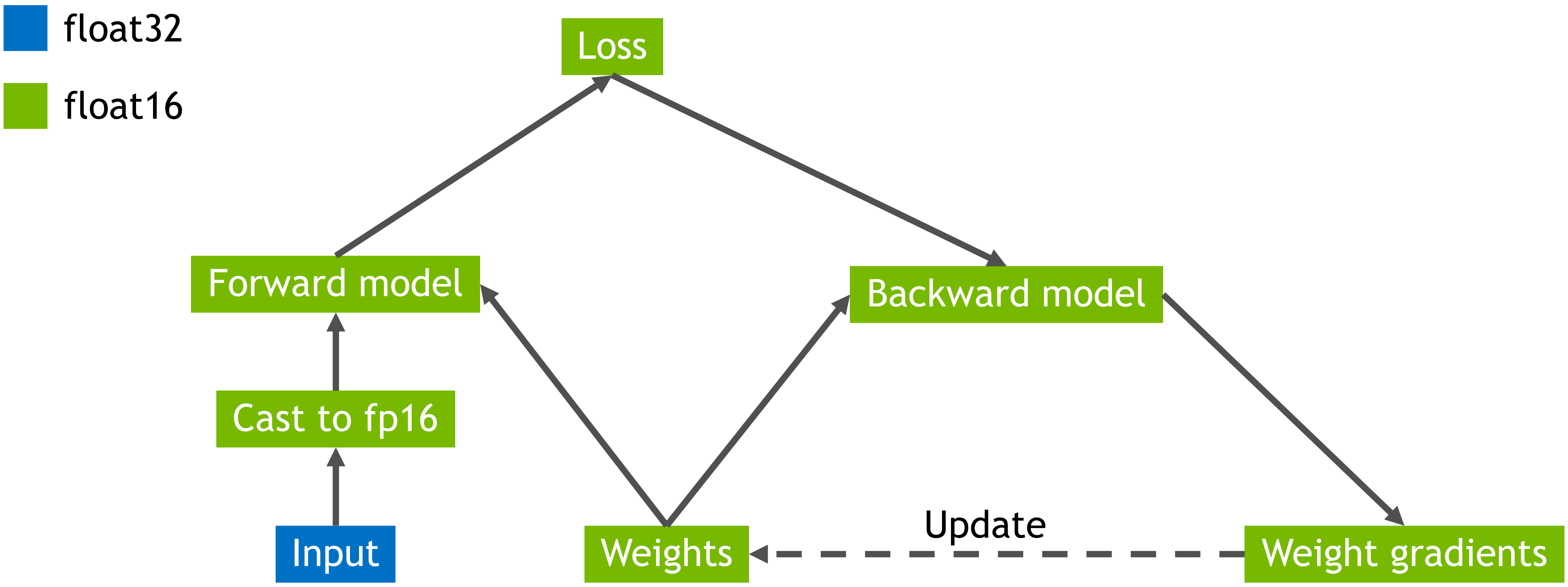

Gradients and variables are float16 too

STEP 1: CONVERSION TO FP16



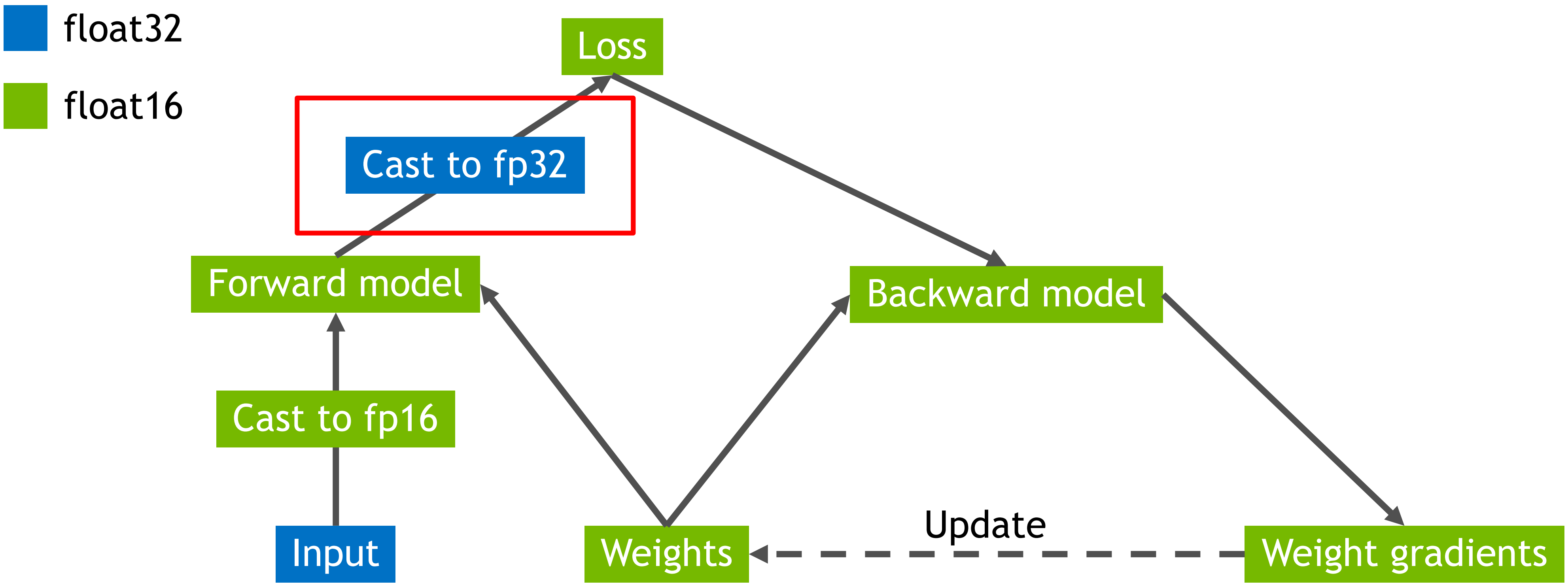
NEW GRAPH


float32
float16
Loss
Forward model
Backward model
Cast to fp16
Input
Weights
Update
Weight gradients

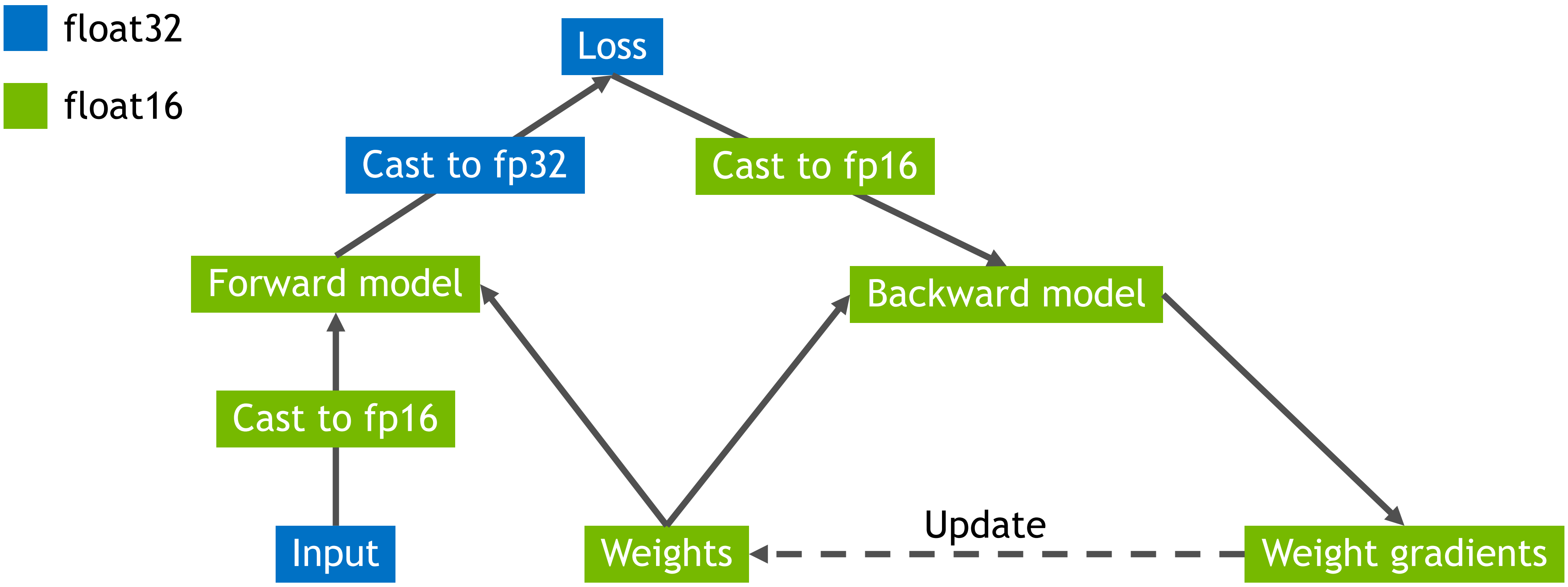
STEP 2: USE FP32 TO COMPUTE THE LOSS

```
def build_training_model(inputs, labels, nlabel):
    inputs    = tf.cast(inputs, tf.float16)
    top_layer = build_forward_model(inputs)
    logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```

STEP 2: USE FP32 TO COMPUTE THE LOSS



NEW GRAPH


float32
float16
Loss
Cast to fp32
Cast to fp16
Forward model
Backward model
Cast to fp16
Input
Weights
Update
Weight gradients

STEP 3: FP32 MASTER WEIGHTS

Helper function

```python
def float32_variable_storage_getter(getter, name, shape=None, dtype=None,
                                    initializer=None, regularizer=None,
                                    trainable=True,
                                    *args, **kwargs):
    """Custom variable getter that forces trainable variables to be stored in
    float32 precision and then casts them to the training precision.
    """
    storage_dtype = tf.float32 if trainable else dtype
    variable = getter(name, shape, dtype=storage_dtype,
                      initializer=initializer, regularizer=regularizer,
                      trainable=trainable,
                      *args, **kwargs)
    if trainable and dtype != tf.float32:
        variable = tf.cast(variable, dtype)
    return variable
```

STEP 3: FP32 MASTER WEIGHTS

Use of helper function

```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```

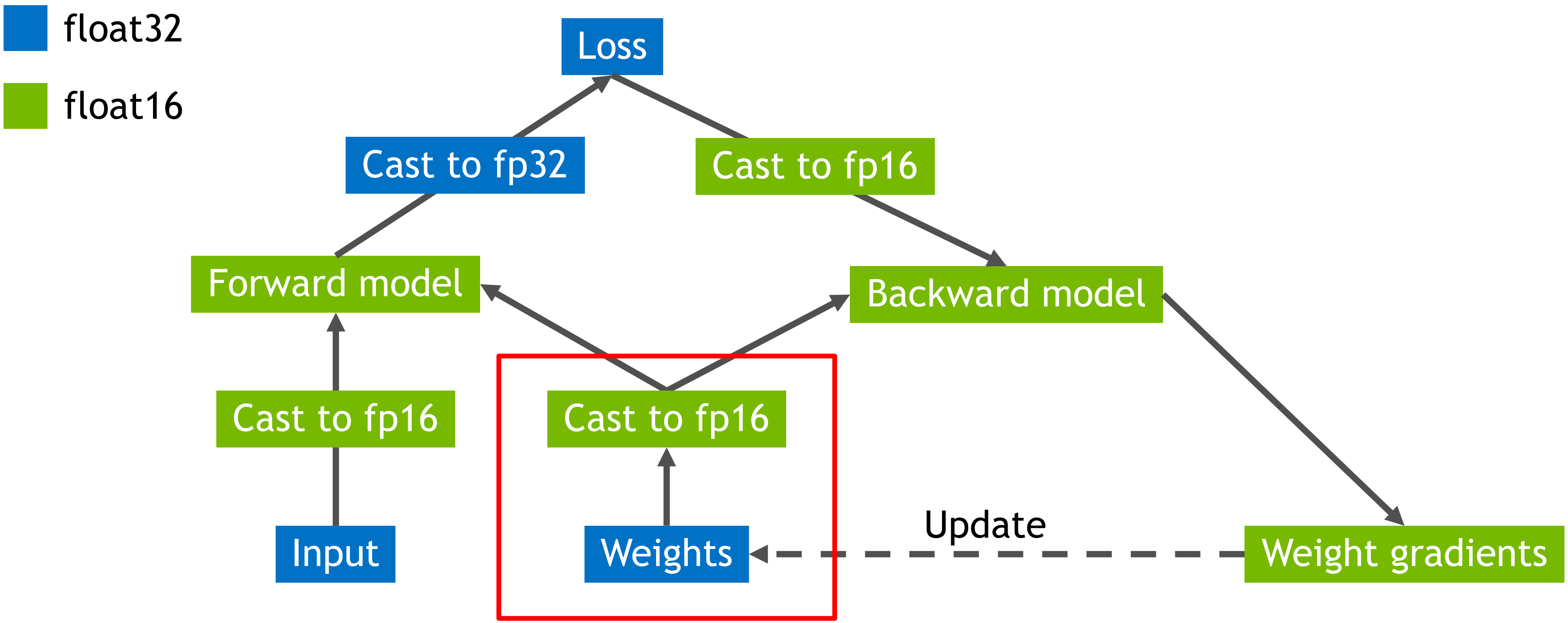
STEP 3: FP32 MASTER WEIGHTS

Use of helper function

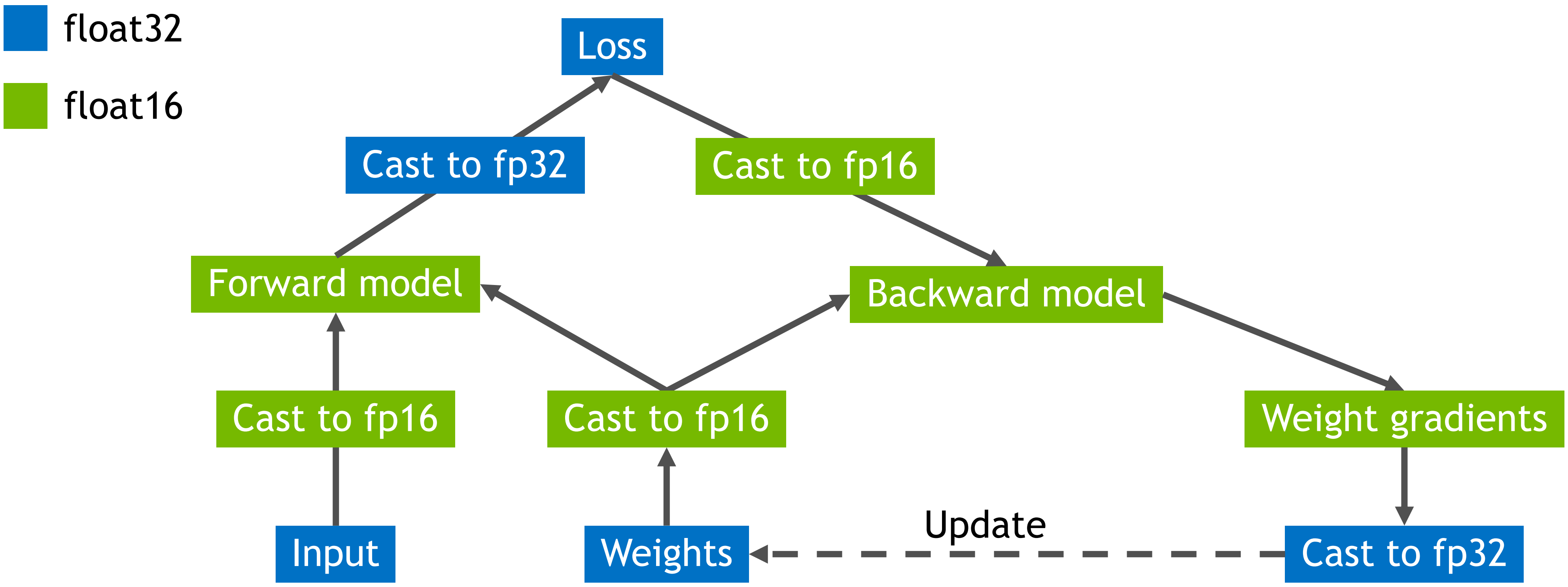
```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    gradvars  = optimizer.compute_gradients(loss)
    train_op  = optimizer.apply_gradients(gradvars)
    return inputs, labels, loss, train_op
```

Gradients and variables are now float32,
but the gradient computations still use float16.

STEP 3: FP32 MASTER WEIGHTS



NEW GRAPH



float32
float16
Loss
Cast to fp32
Cast to fp16
Forward model
Backward model
Cast to fp16
Cast to fp16
Weight gradients
Input
Weights
Update
Cast to fp32

STEP 4: LOSS (GRADIENT) SCALING

Avoid gradient underflow

```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    loss_scale = 128.0 # Value may need tuning depending on the model
    gradients, variables = zip(*optimizer.compute_gradients(loss * loss_scale))
    gradients = [grad / loss_scale for grad in gradients]
    train_op  = optimizer.apply_gradients(zip(gradients, variables))
    return inputs, labels, loss, train_op
```

STEP 4: LOSS (GRADIENT) SCALING

Avoid gradient underflow

```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
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    gradients, variables = zip(*optimizer.compute_gradients(loss * loss_scale))
    gradients = [grad / loss_scale for grad in gradients]
    train_op  = optimizer.apply_gradients(zip(gradients, variables))
    return inputs, labels, loss, train_op
```
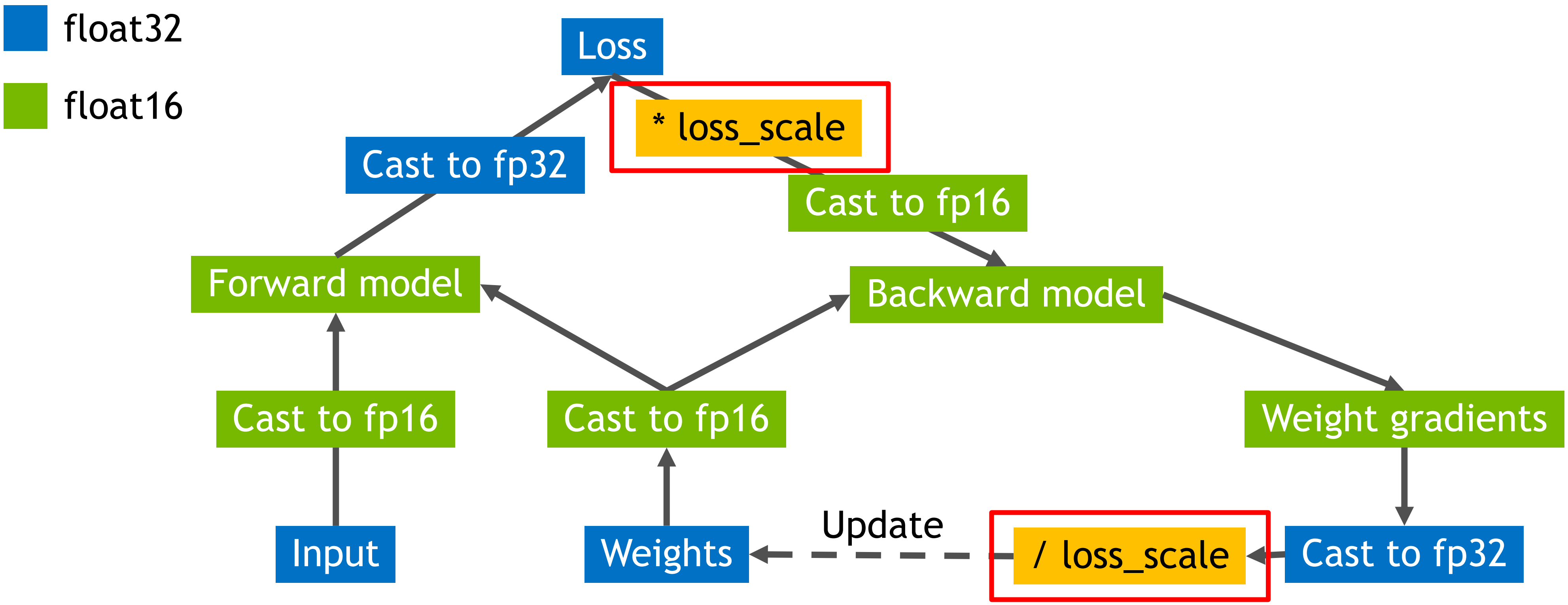
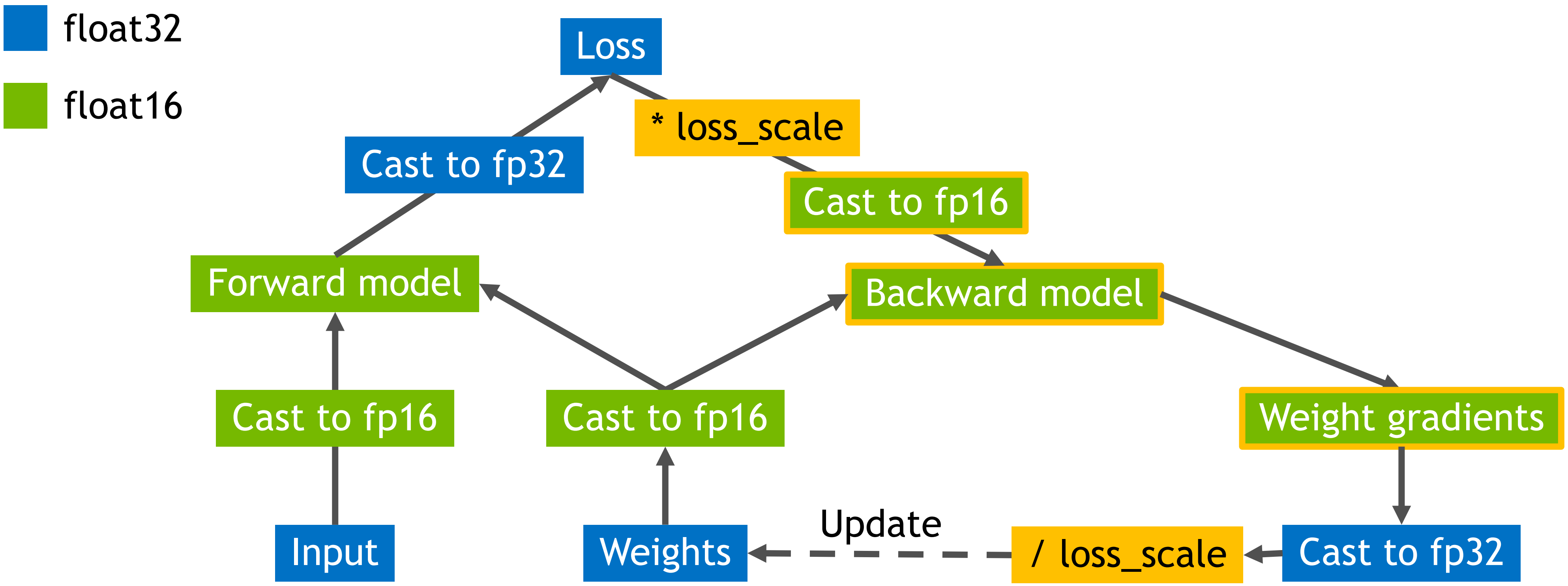

Raises exponent during bwd pass in float16

Returns gradients (now float32)
to correct exponent

STEP 4: LOSS (GRADIENT) SCALING



NEW GRAPH



float32
float16
Loss
* loss_scale
Cast to fp32
Cast to fp16
Forward model
Backward model
Cast to fp16
Cast to fp16
Weight gradients
Input
Weights
Update
/ loss_scale
Cast to fp32

OPTIONAL EXTRA: GRADIENT CLIPPING

```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    loss_scale = 128.0 # Value may need tuning depending on the model
    gradients, variables = zip(*optimizer.compute_gradients(loss * loss_scale))
    gradients = [grad / loss_scale for grad in gradients]
    gradients, _ = tf.clip_by_global_norm(gradients, 5.0)
    train_op  = optimizer.apply_gradients(zip(gradients, variables))
    return inputs, labels, loss, train_op
```

ALL TOGETHER

```
def build_training_model(inputs, labels, nlabel):
    inputs = tf.cast(inputs, tf.float16)
    with tf.variable_scope('fp32_vars', custom_getter=float32_variable_storage_getter):
        top_layer = build_forward_model(inputs)
        logits    = tf.layers.dense(top_layer, nlabel, activation=None)
    logits    = tf.cast(logits, tf.float32)
    loss      = tf.losses.sparse_softmax_cross_entropy(logits=logits, labels=labels)
    optimizer = tf.train.MomentumOptimizer(learning_rate=0.01, momentum=0.9)
    loss_scale = 128.0 # Value may need tuning depending on the model
    gradients, variables = zip(*optimizer.compute_gradients(loss * loss_scale))
    gradients = [grad / loss_scale for grad in gradients]
    gradients, _ = tf.clip_by_global_norm(gradients, 5.0)
    train_op  = optimizer.apply_gradients(zip(gradients, variables))
    return inputs, labels, loss, train_op
```

CONCLUSIONS

Mixed precision training is now well supported by deep learning frameworks

Conversion requires < 10 lines of code for most training scripts

For more info and frameworks, see our Mixed Precision Training guide:

https://docs.nvidia.com/deeplearning/sdk/mixed-precision-training/index.html

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