AUTOMATIC MIXED PRECISION IN PYTORCH

Michael Carilli and Michael Ruberry, 3/20/2019

THIS TALK

Using mixed precision and Volta/Turing your networks can be:

1. 2-4x faster
2. more memory-efficient
3. just as powerful

with no architecture change.

REFERENCES

Myle Ott and Sergey Edunov, *Taking Advantage of Mixed Precision to Accelerate Training Using PyTorch*, GTC 2019 Session 9832
Right after this talk in Room 210D

Carl Case, *Mixed Precision Training of Deep Neural Networks*, GTC 2019 Session 9143

Sharan Narang, Paulius Micikevicius *et al.*, *Mixed Precision Training*, ICLR 2018

Automatic Mixed Precision (AMP) for Pytorch is part of NVIDIA Apex:
https://github.com/nvidia/apex
https://nvidia.github.io/apex/

TALK OVERVIEW

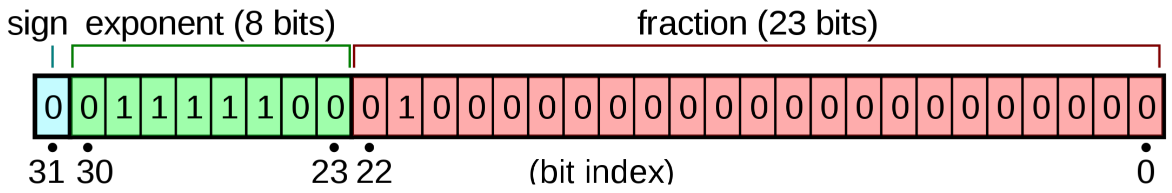
1. Introduction to Mixed Precision Training
2. Automatic Mixed Precision (AMP) for PyTorch
3. Mixed Precision Principles in AMP
4. Tensor Core Performance Tips

INTRODUCTION TO MIXED PRECISION TRAINING

FP32 AND FP16

FP32

8-bit exponent, 23-bit mantissa

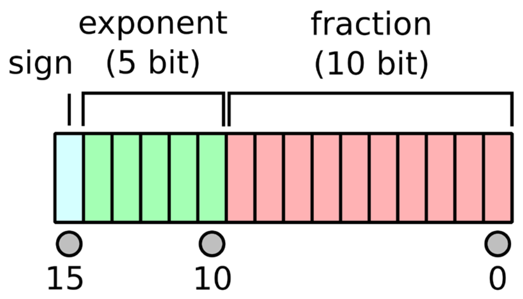


Dynamic range:

$1.4 \times 10^{-45} < x < 3.4 \times 10^{38}$

FP16

5-bit exponent, 10-bit mantissa



Dynamic range:

$5.96 \times 10^{-8} < x < 65504$

MAXIMIZING MODEL PERFORMANCE

FP16 is fast and memory-efficient.

FP32	**FP16** with Tensor Cores
1x compute throughput	**8X** compute throughput
1x memory throughput	**2X** memory throughput
1x memory storage	**1/2X** memory storage

MAXIMIZING MODEL PERFORMANCE

FP16 input enables Volta/Turing Tensor Cores.

FP16 Input, FP32 Accumulate, FP16 Output for GEMMs and Convolutions

$$\underset{\text{FP16 or FP32}}{D} = \left(\underset{\text{FP16}}{\begin{bmatrix} A_{0,0} & A_{0,1} & A_{0,2} & A_{0,3} \\ A_{1,0} & A_{1,1} & A_{1,2} & A_{1,3} \\ A_{2,0} & A_{2,1} & A_{2,2} & A_{2,3} \\ A_{3,0} & A_{3,1} & A_{3,2} & A_{3,3} \end{bmatrix}} \right) \left(\underset{\text{FP16}}{\begin{bmatrix} B_{0,0} & B_{0,1} & B_{0,2} & B_{0,3} \\ B_{1,0} & B_{1,1} & B_{1,2} & B_{1,3} \\ B_{2,0} & B_{2,1} & B_{2,2} & B_{2,3} \\ B_{3,0} & B_{3,1} & B_{3,2} & B_{3,3} \end{bmatrix}} \right) + \left(\underset{\text{FP16 or FP32}}{\begin{bmatrix} C_{0,0} & C_{0,1} & C_{0,2} & C_{0,3} \\ C_{1,0} & C_{1,1} & C_{1,2} & C_{1,3} \\ C_{2,0} & C_{2,1} & C_{2,2} & C_{2,3} \\ C_{3,0} & C_{3,1} & C_{3,2} & C_{3,3} \end{bmatrix}} \right)$$

125 TFlops Throughput: 8X more than FP32 on Volta V100

MAXIMIZING MODEL PERFORMANCE

FP32 offers precision and range benefits.

FP32	FP16
Wider dynamic range	Narrower dynamic range
Increased precision captures small accumulations	Reduced precision may lose small accumulations

MAXIMIZING MODEL PERFORMANCE

Certain ops require FP32 dynamic range.

Reductions, exponentiation

```
a = torch.cuda.HalfTensor(4096)
a.fill_(16.0)
a.sum()
```

→ inf

```
b = torch.cuda.FloatTensor(4096)
b.fill_(16.0)
b.sum()
```

→ 65,536

MAXIMIZING MODEL PERFORMANCE

Addition of large + small values benefits from FP32 precision.

Weight updates, reductions again

$1 + 0.0001 = ??$

```
param = torch.cuda.HalfTensor([1.0])
update = torch.cuda.HalfTensor([.0001])
print(param + update)
```

$\longrightarrow$ 1

In FP16, when *update/param* < $2^{-11} \approx 0.00049$, update has no effect.

```
param = torch.cuda.FloatTensor([1.0])
update = torch.cuda.FloatTensor([.0001])
print(param + update)
```

$\longrightarrow$ 1.0001

MAXIMIZING MODEL PERFORMANCE

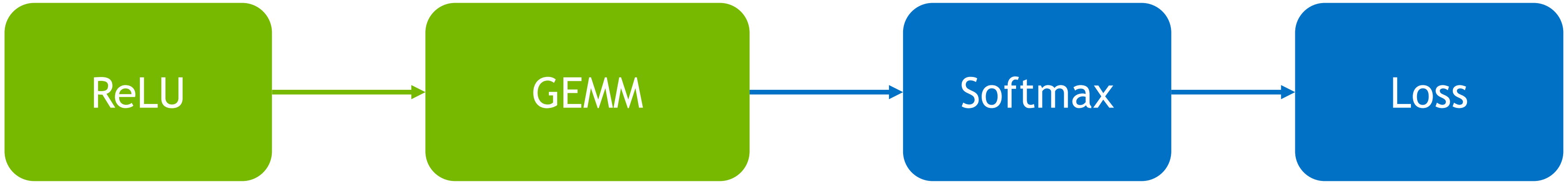
Assign each operation its optimal precision.

FP16

- GEMMs + Convolutions can use Tensor Cores
- Most pointwise ops (e.g. add, multiply): 1/2X memory storage for intermediates, 2X memory throughput

FP32

- Weight updates benefit from precision
- Loss functions (often reductions) benefit from precision and range
- Softmax, norms, some other ops benefit from precision and range



MIXED PRECISION IN PRACTICE: SPEED

Single Volta, FP32 vs Mixed Precision

Nvidia Sentiment Analysis**: **4.5X** speedup

** https://github.com/NVIDIA/sentiment-discovery

MIXED PRECISION IN PRACTICE: SPEED

Single Volta, FP32 vs Mixed Precision

Nvidia Sentiment Analysis**: **4.5X** speedup

FAIRseq: **4X** speedup

** https://github.com/NVIDIA/sentiment-discovery

MIXED PRECISION IN PRACTICE: SPEED

Single Volta, FP32 vs Mixed Precision

Nvidia Sentiment Analysis**: **4.5X** speedup

FAIRseq: **4X** speedup

GNMT: **2X** speedup

** https://github.com/NVIDIA/sentiment-discovery

MIXED PRECISION IN PRACTICE: ACCURACY

Same accuracy as FP32, with no hyperparameter changes.

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%

ILSVRC12 classification top-1 accuracy.
(Sharan Narang, Paulius Micikevicius *et al.*, "Mixed Precision Training", ICLR 2018)
**Same hyperparameters and learning rate schedule as FP32.

AMP FOR PYTORCH

AMP: AUTOMATIC MIXED PRECISION

Existing FP32 (default) script

->

Add 2 lines of Python

->

Accelerate your training with mixed precision

EXAMPLE

```
N, D_in, D_out = 64, 1024, 512
x = torch.randn(N, D_in, device="cuda")
y = torch.randn(N, D_out, device="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()
```

EXAMPLE

```
N, D_in, D_out = 64, 1024, 512
x = torch.randn(N, D_in, device="cuda")
y = torch.randn(N, D_out, device="cuda")

model = torch.nn.Linear(D_in, D_out).cuda()
optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)
model, optimizer = amp.initialize(model, optimizer, opt_level="O1")

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

    optimizer.zero_grad()
    with amp.scale_loss(loss, optimizer) as scaled_loss:
        scaled_loss.backward()
    optimizer.step()
```

AMP.INITIALIZE()

Sets up your model(s) and optimizer(s) for mixed precision training.

```
model, optimizer = amp.initialize(model, optimizer,
                       opt_level,
```

Required. Establishes a default set of under-the-hood properties that govern the chosen mode.

```
                       cast_model_type=None,
                       patch_torch_functions=None,
                       keep_batchnorm_fp32=None,
                       master_weights=None,
                       loss_scale = None)
```

Optional property overrides, for finer-grained control

OPTIMIZATION LEVELS

OPT_LEVEL="O0"

FP32 training.
Your incoming model should be FP32 already, so this is likely a no-op. O0 can be useful to establish an accuracy baseline.

O1

Mixed Precision.
Patches Torch functions to internally carry out Tensor Core-friendly ops in FP16, and ops that benefit from additional precision in FP32. Also uses dynamic loss scaling. **Because casts occur in functions, model weights remain FP32.**

O2

"Almost FP16" Mixed Precision.
FP16 model and data with FP32 batchnorm, FP32 master weights, and dynamic loss scaling. **Model weights, except batchnorm weights, are cast to FP16.**

O3

FP16 training.
O3 can be useful to establish the "speed of light" for your model. If your model uses batch normalization, add **`keep_batchnorm_fp32=True`**, which enables cudnn batchnorm.

NO MANUAL CASTS NEEDED

```
N, D_in, D_out = 64, 1024, 512
x = torch.randn(N, D_in, device="cuda")
y = torch.randn(N, D_out, device="cuda")

model = torch.nn.Linear(D_in, D_out).cuda()
optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)
model, optimizer = amp.initialize(model, optimizer, opt_level="O0")

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

    optimizer.zero_grad()
    with amp.scale_loss(loss, optimizer) as scaled_loss:
        scaled_loss.backward()
    optimizer.step()
```

No need to manually cast your model or data, regardless of `opt_level`

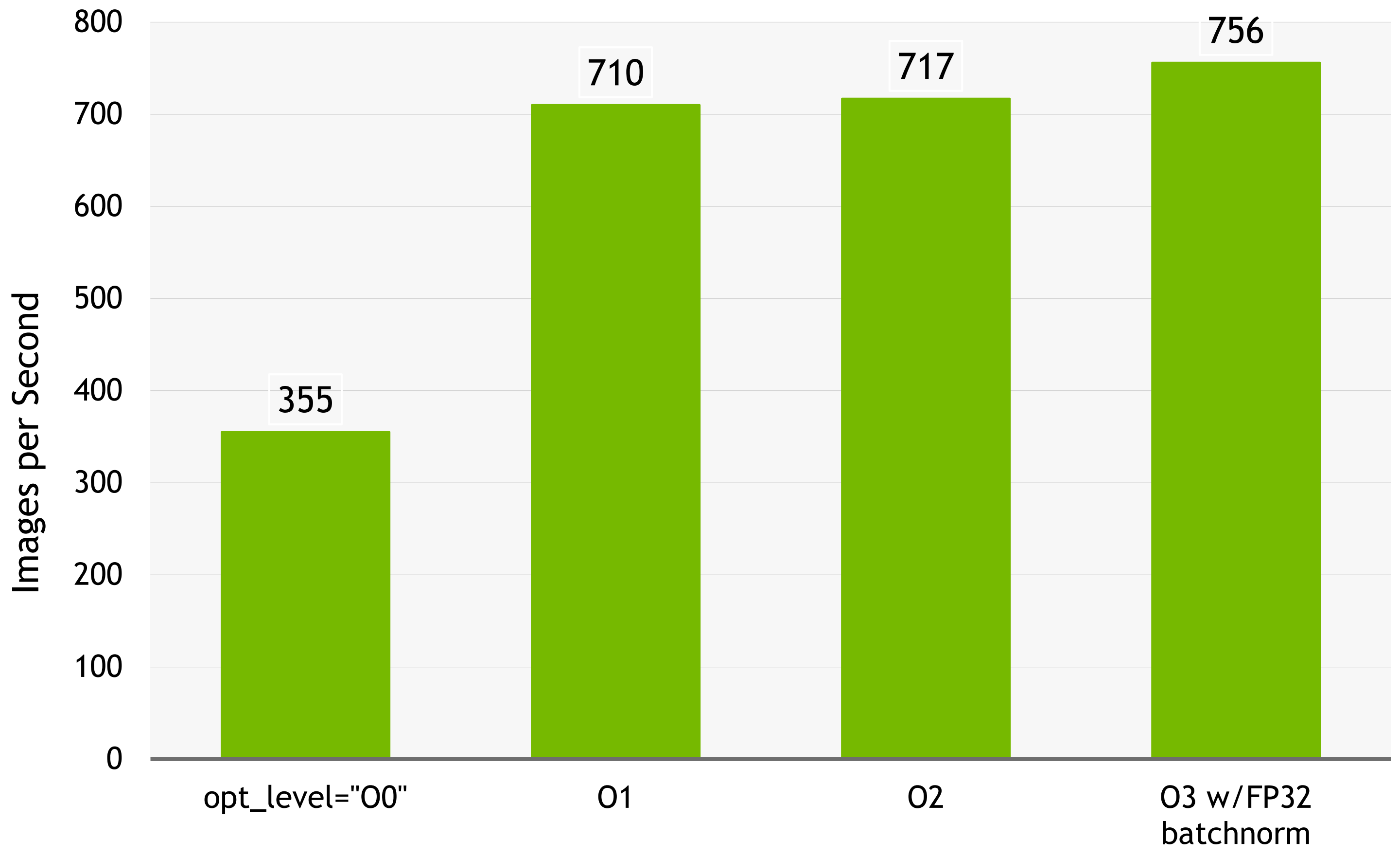
No need to manually cast your output or target, regardless of `opt_level`

OPTIMIZATION LEVELS IN ACTION

https://github.com/NVIDIA/apex/tree/master/examples/imagenet

Mixed Precision (O1 and O2)

- 2X faster than FP32
- Only ~6% overhead relative to “speed of light”



Timings on NVIDIA Volta V100 32GB

On 8 Voltas, O0 converged to 76.15%, O1 converged to 76.38%, O2 converged to 75.9%

MIXED PRECISION GUIDANCE

1. O0 (FP32) first to establish an accuracy baseline.
2. Try O1 to enable mixed precision.
3. For the adventurous, try O2 or O3, which may improve speed.
4. Experiment! The AMP API makes it easy to try different mixed precision modes and properties.

MIXED PRECISION PRINCIPLES IN AMP

MIXED PRECISION TRAINING PRINCIPLES

1. Accumulate in FP32.

2. Represent values in the appropriate dynamic range.

FP32 WEIGHTS

Weight updates are an accumulation.

$1 + 0.0001 = ??$

```
param = torch.cuda.HalfTensor([1.0])
update = torch.cuda.HalfTensor([.0001])
print(param + update)
```

→ 1

In FP16, when *update/param* $< 2^{-11} \approx 0.00049$, update has no effect.

```
param = torch.cuda.FloatTensor([1.0])
update = torch.cuda.FloatTensor([.0001])
print(param + update)
```

→ 1.0001

MIXED PRECISION TRAINING PRINCIPLES

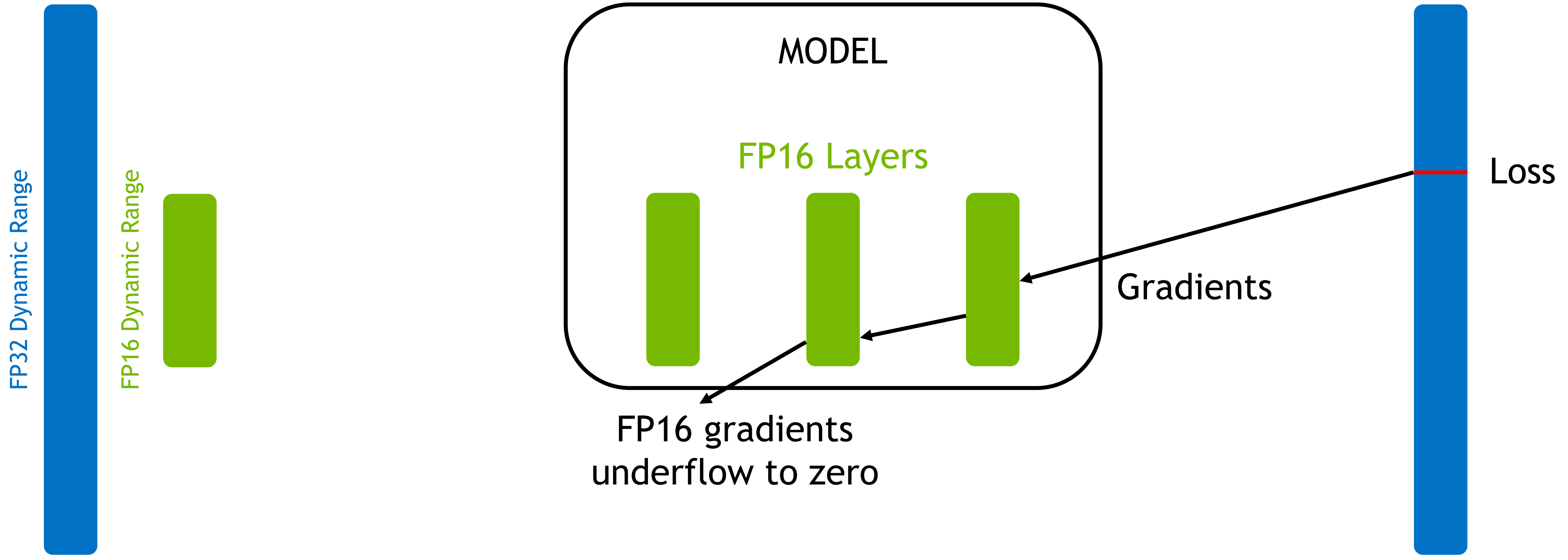
1. Accumulate in FP32.

    AMP maintains weights in FP32.

2. Represent values in the appropriate dynamic range.

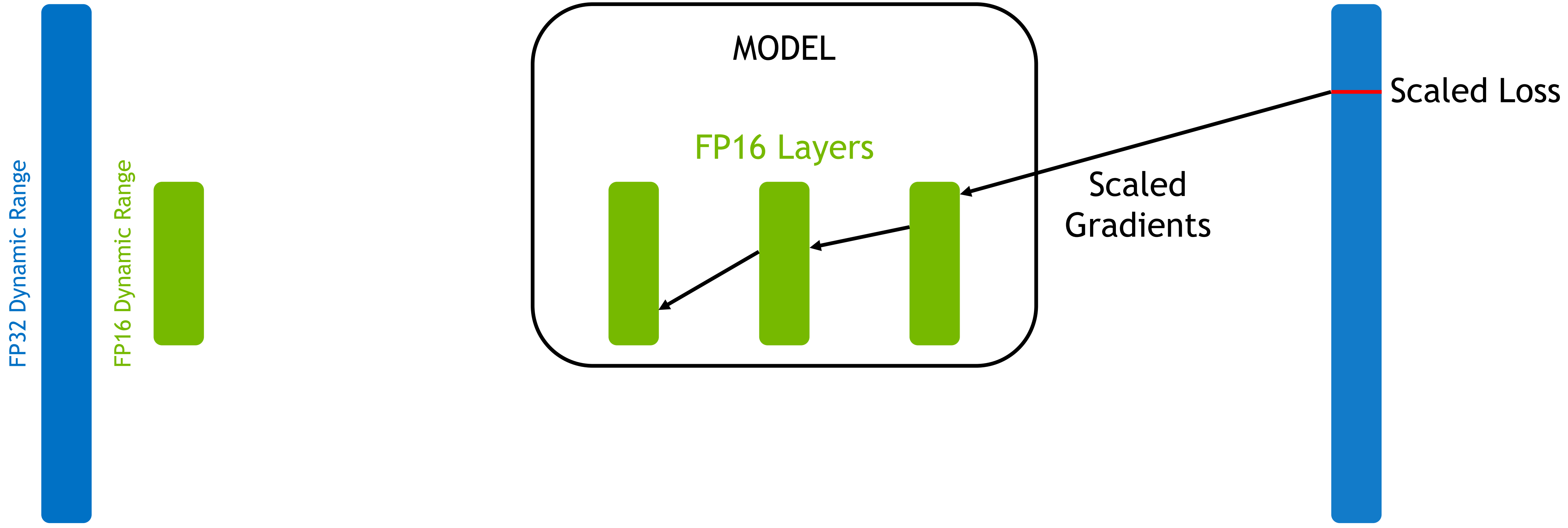
GRADIENT UNDERFLOW

Small gradients may underflow in FP16 regions of the network.



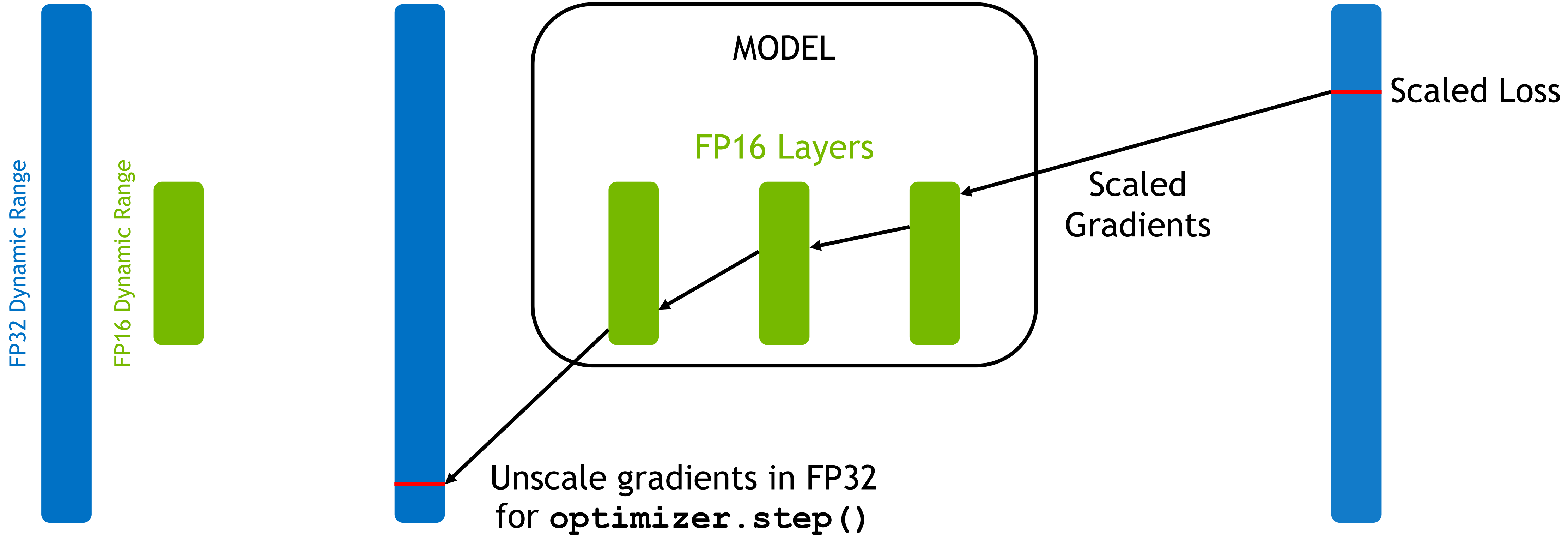
LOSS SCALING

Scaling the loss brings gradients into the FP16 dynamic range.



LOSS SCALING

Scaling the loss brings gradients into the FP16 dynamic range.



LOSS SCALING

Scaling the loss brings gradients into the FP16 dynamic range.

1. Multiply the loss by some constant S.
   `scaled_loss = loss*S`

2. `scaled_loss.backward()`
   By the chain rule, gradients will also be scaled by S.
   This preserves small gradient values.

3. Unscale gradients before `optimizer.step()`.**

** Unscaling ensures loss scaling does not affect the learning rate.   Loss scaling does not require retuning the learning rate.

MIXED PRECISION TRAINING PRINCIPLES

1. Accumulate in FP32.

   AMP maintains weights in FP32.

2. Represent values in the appropriate dynamic range.

   AMP scales the network’s gradients.

OPT_LEVELS AND PROPERTIES

Each opt_level establishes a set of properties:

`cast_model_type (torch.dtype)`
Cast your model's parameters and buffers to the desired type.

`patch_torch_functions (True or False)`
Patch all Torch functions to perform Tensor Core-friendly ops in FP16,
and any ops that benefit from FP32 precision in FP32.

`keep_batchnorm_fp32 (True or False)`
Maintain batchnorms in the desired type (typically **`torch.float32`**).

`master_weights (True or False)`
Maintain FP32 master weights for any FP16 model weights (applies to **`opt_level="O2"`**).

`loss_scale (float, or "dynamic")`
If **`loss_scale`** is a float value, use this value as the static (fixed) loss scale. Otherwise,
automatically adjust the loss scale as needed.

OPT_LEVELS AND PROPERTIES

O0

FP32 training.
Your incoming model should be FP32 already, so this is likely a no-op. O0 can be useful to establish an accuracy baseline.

```
cast_model_type=torch.float32
patch_torch_functions=False
keep_batchnorm_fp32=None**
master_weights=False
loss_scale=1.0
```

** None indicates “not applicable.”

O1

Mixed Precision.
Patches Torch functions to internally carry out Tensor Core-friendly ops in FP16, and ops that benefit from additional precision in FP32. Also uses dynamic loss scaling. **Because casts occur in functions, model weights remain FP32.**

```
cast_model_type=None
patch_torch_functions=True
keep_batchnorm_fp32=None
master_weights=None**
loss_scale=“dynamic”
```

** Separate FP32 master weights are not applicable because the weights remain FP32.

O1 (PATCH_TORCH_FUNCTIONS)

Patches `torch.*` functions to cast their inputs to the optimal type.

Ops that are fast and stable on Tensor Cores (GEMMs and Convolutions) run in FP16.

Ops that benefit from FP32 precision (softmax, exponentiation, pow) run in FP32.

```
model, optim =
amp.initialize(model, optim,
               opt_level="O1")
```

Conceptual operation of patching:

```
for func in fp16_cast_list:
    def create_casting_func(old_func):
        def func_with_fp16_cast(input):
            return old_func(input.half())
        return func_with_cast
    torch.func = create_casting_func(torch.func)

for func in fp32_cast_list:
    def create_casting_func(old_func):
        def func_with_fp32_cast(input):
            return old_func(input.half())
        return func_with_cast
    torch.func = create_casting_func(torch.func)
```

OPT_LEVELS AND PROPERTIES

O2

"Almost FP16" Mixed Precision.
FP16 model and data with FP32 batchnorm, FP32 master weights, and dynamic loss scaling. **Model weights, except batchnorm weights, are cast to FP16.**

```
cast_model_type=torch.float16
patch_torch_functions=False
keep_batchnorm_fp32=True
master_weights=True
loss_scale="dynamic"
```

O3

FP16 training.
O3 can be useful to establish the "speed of light" for your model. If your model uses batch normalization, add the manual override **`keep_batchnorm_fp32=True`**, which enables cudnn batchnorm.

```
cast_model_type=torch.float16
patch_torch_functions=False
keep_batchnorm_fp32=False
master_weights=False
loss_scale=1.0
```

OPT_LEVELS AND PROPERTIES

Properties for a given opt_level can be individually overridden.

```
model, optimizer = amp.initialize(model, optimizer,
                   opt_level="O1",
                   loss_scale=128.0)
```

Sets up `loss_scale="dynamic"` by default.

Optional override: Tells Amp to use a static loss scale of 128.0 instead.

OPT_LEVELS AND PROPERTIES

Properties for a given opt_level can be individually overridden.

```
model, optimizer = amp.initialize(model, optimizer,
                  opt_level="O1",
                  loss_scale=128.0)
```

`opt_level="O1",` } Sets up `loss_scale="dynamic"` by default.

`loss_scale=128.0)` } Optional override: Tells AMP to use a static loss scale of 128.0 instead.

AMP will issue a warning and explanation if you attempt to override a property that does not make sense.

For example, setting `opt_level="O1"` and the override `master_weights=True` does not make sense.

EXAMPLE REVISITED

```
N, D_in, D_out = 64, 1024, 512
x = torch.randn(N, D_in, device="cuda")
y = torch.randn(N, D_out, device="cuda")

model = torch.nn.Linear(D_in, D_out).cuda()
optimizer = torch.optim.SGD(model.parameters(), lr=1e-3)
model, optimizer = amp.initialize(model, optimizer, opt_level="O1")

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

    optimizer.zero_grad()
    with amp.scale_loss(loss, optimizer) as scaled_loss:
        scaled_loss.backward()
    optimizer.step()
```

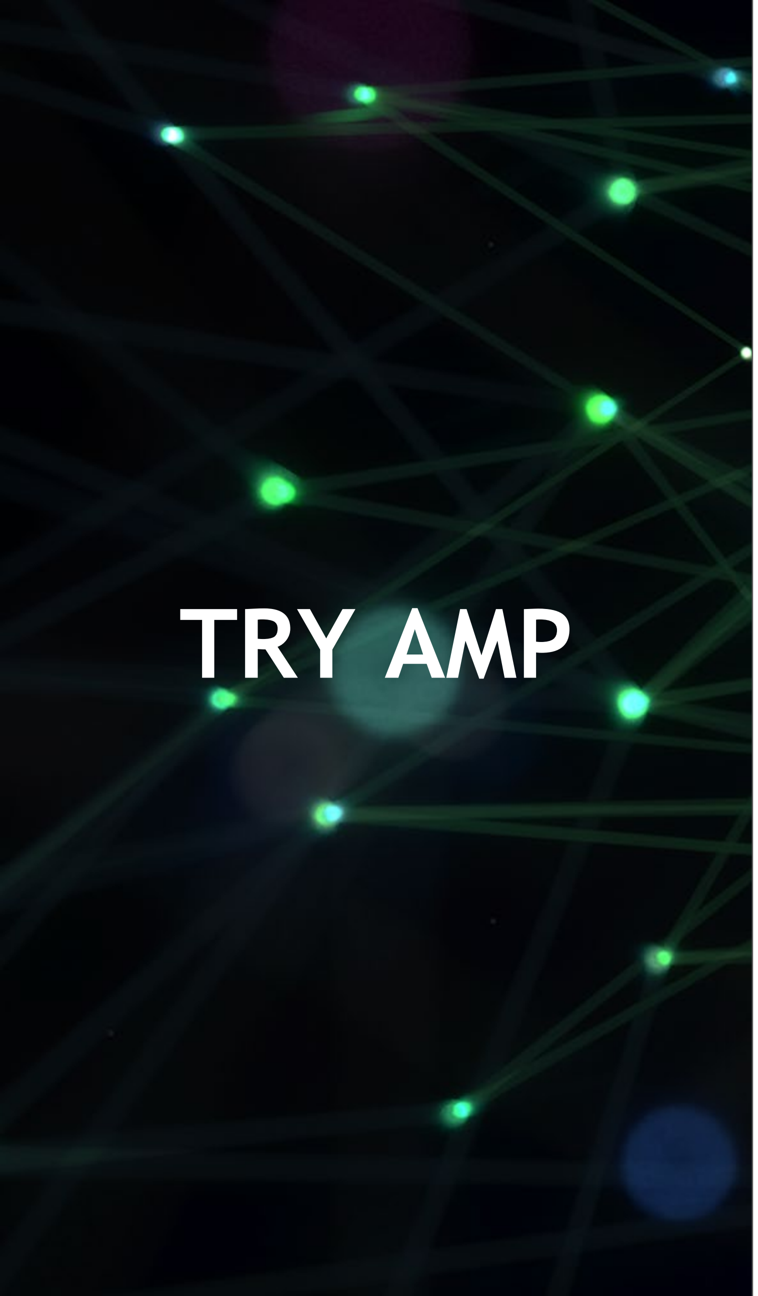
AMP OPERATION SUMMARY

AMP casts weights and/or patches Torch functions based on **`opt_level`** and properties:

```
model, optimizer = amp.initialize(model, optimizer, opt_level=“O1”)
```

AMP applies loss scaling as appropriate for the **`opt_level`** and properties:

```
with amp.scale_loss(loss, optimizer) as scaled_loss:
    scaled_loss.backward()
```



TRY AMP

Available through the NVIDIA Apex repository of mixed precision and distributed tools:
https://github.com/nvidia/apex

Full API documentation:
https://nvidia.github.io/apex/

For more on mixed precision, don’t forget to see:

Myle Ott and Sergey Edunov, *Taking Advantage of Mixed Precision to Accelerate Training Using PyTorch*, GTC 2019 Session 9832
Right after this talk in Room 210D

Carl Case, *Mixed Precision Training of Deep Neural Networks*, GTC 2019 Session 9143

TENSOR CORE PERFORMANCE TIPS

TENSOR CORE PERFORMANCE TIPS

- GEMMs = “generalized (dense) matrix-matrix multiplies”:
  For A x B where A has size (M, K) and B has size (K, N):
  N, M, K should be multiples of 8.
- GEMMs in fully connected layers:
  Batch size, input features, output features should be multiples of 8.
- GEMMs in RNNs:
  Batch size, hidden size, embedding size, and dictionary size 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 Pytorch's autotuner.

The first iteration, it will test different cuDNN algorithms for each new convolution size it sees, and cache the fastest choice to use in later iterations.

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

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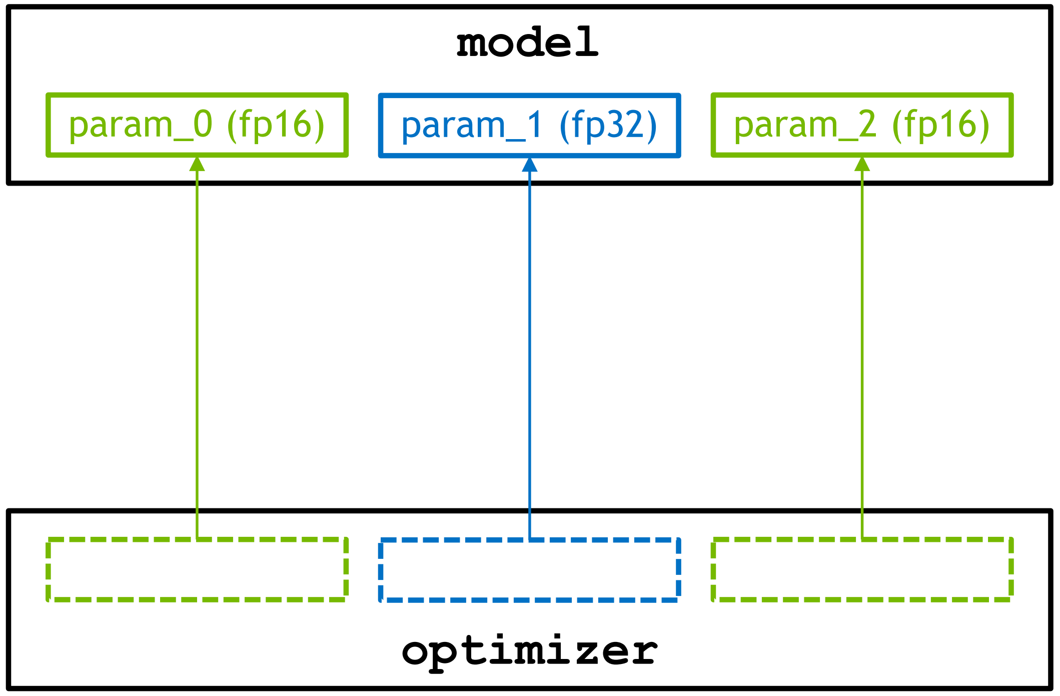
ENSURING FP32 WEIGHT UPDATES

```
optimizer = torch.optim.SGD(model.parameters())
model, optimizer = amp.initialize(model, optimizer, opt_level="O2")
```

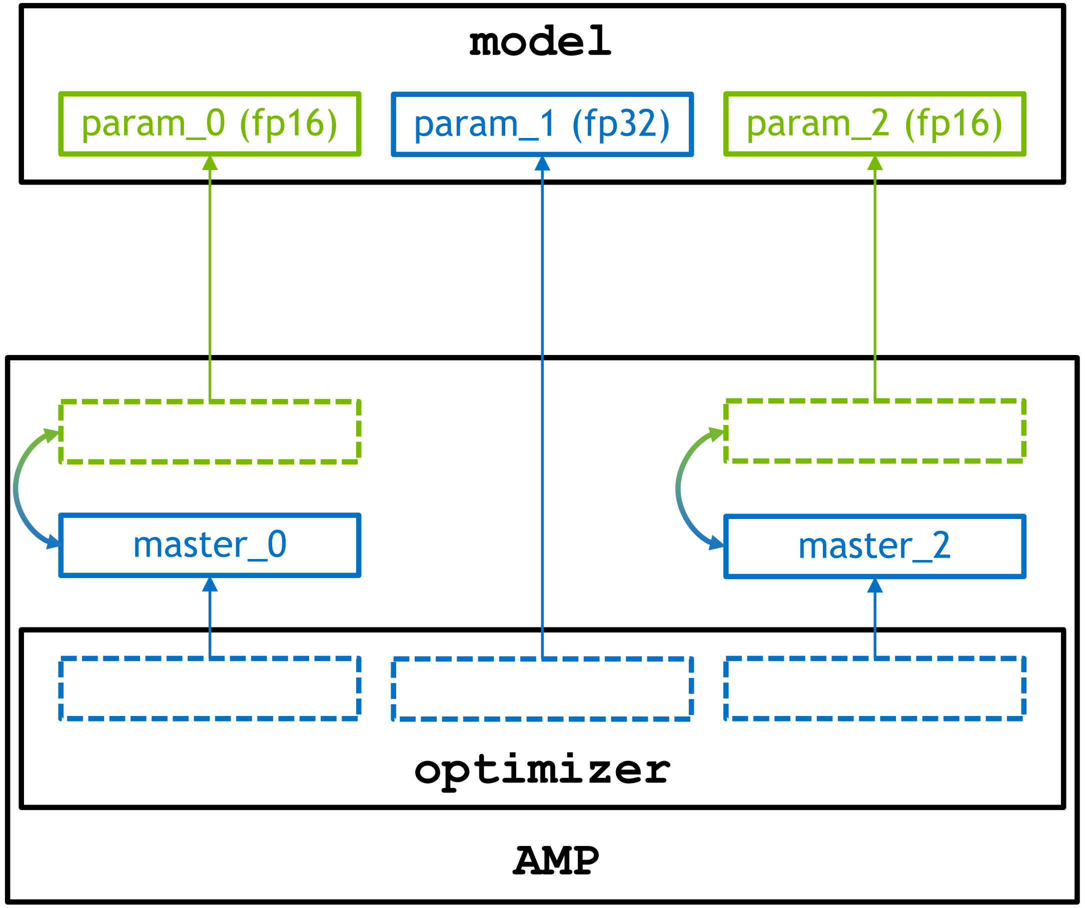
After casting requested by `O2`, **`model`** may contain a mixture of fp16 and fp32 params.



`optimizer` references point to model params.

ENSURING FP32 WEIGHT UPDATES

```
optimizer = torch.optim.SGD(model.parameters())
model, optimizer = amp.initialize(model, optimizer, opt_level="O2")
```



With `O2`, AMP maintains FP32 master params for any FP16 params

Patches optimizer's references to point to master params. `optimizer.step()` acts on master params.