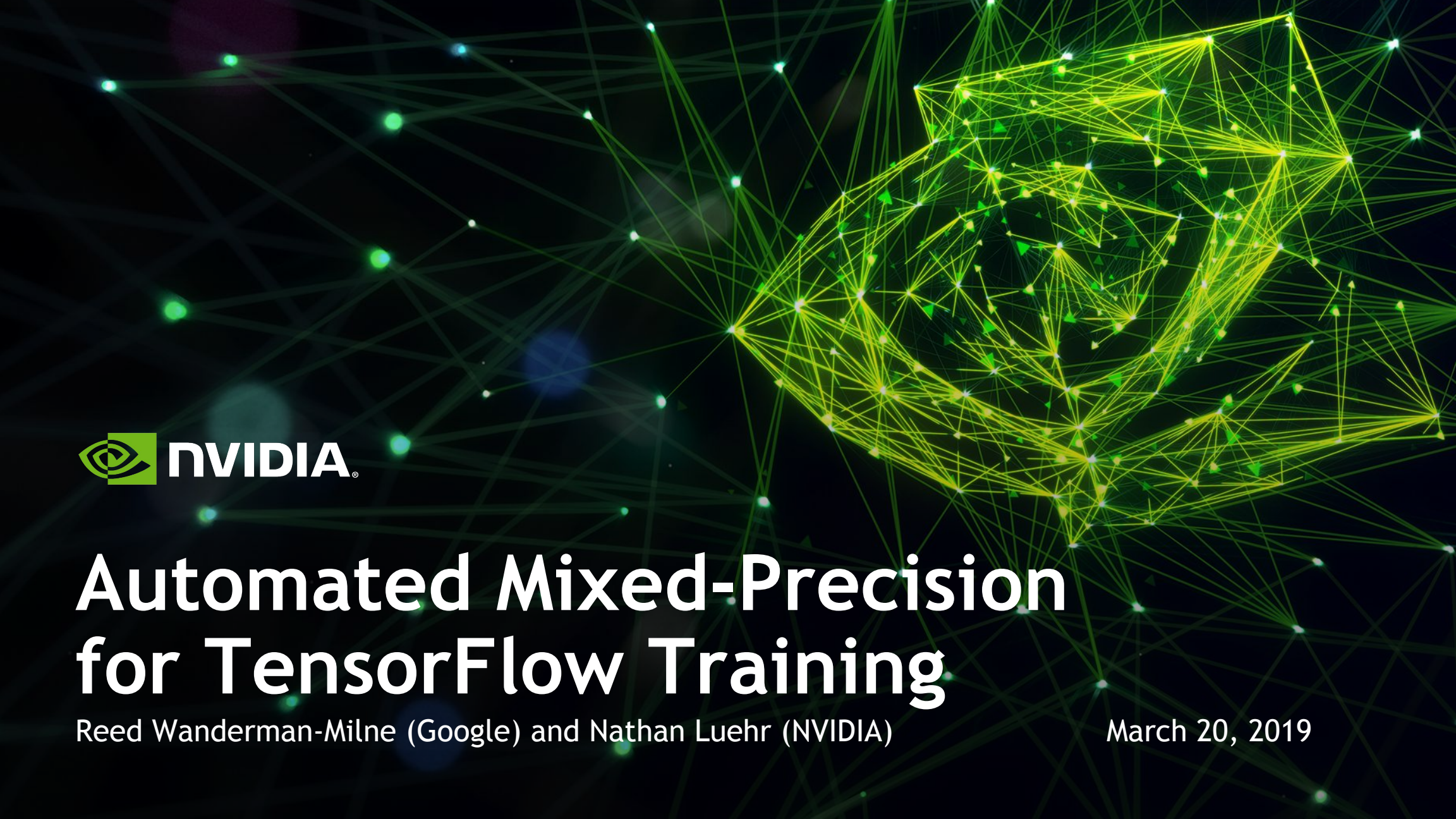

Automated Mixed-Precision for TensorFlow Training

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March 20, 2019

Mixed Precision Training Background

What is Mixed Precision?

Using a mix of float32 and float16 precisions

float16 is much faster on accelerators

Model parameters and some layers need float32 for numerical stability

Loss scaling needed to shift gradient computation into half representable range

Mixed precision improves performance by 1.5-3x on Volta GPUs

Mixed Precision Training Background

Mixed Precision in TensorFlow

tf.keras API

- Keras is the recommended API for training and inference in TensorFlow 2.0
- Allows direct control of layer types
- API not complete yet, but actively being worked on

Automatic Mixed Precision Graph Optimizer

- Single precision graph is converted to mixed precision at runtime
- Does not require tf.keras and will work with your existing TensorFlow 1.x models

Outline

Mixed Precision in tf.keras

- Model Construction
- Automatic Loss Scaling

Automatic Mixed Precision Graph Optimizer

- Graph conversion
- Automatic Loss Scaling

Results


Mixed Precision
in tf.keras

tf.keras API

- Will just need one line:
  tf.keras.mixed_precision.experimental.set_policy("default_mixed")

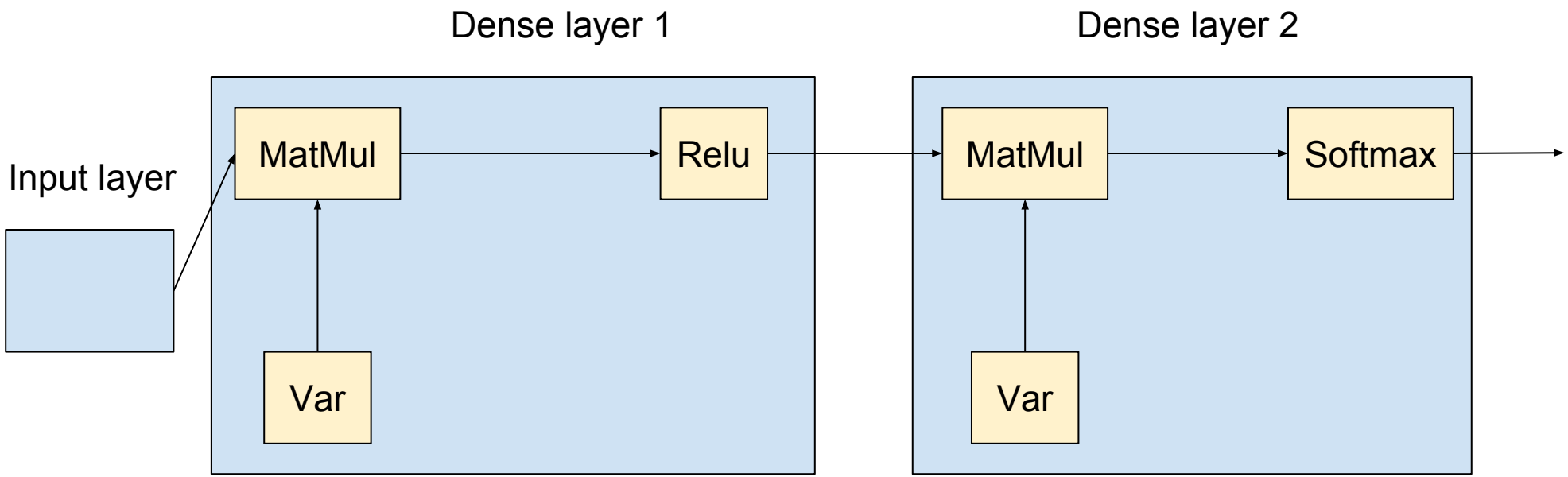
```
tf.keras.mixed_precision.experimental.set_policy("default_mixed")

model = tf.keras.layers.Sequential()
model.add(tf.keras.layers.Dense(32, activation="relu"))
model.add(tf.keras.layers.Dense(32, activation="softmax"))
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

- TensorFlow will automatically choose what to do in each dtype

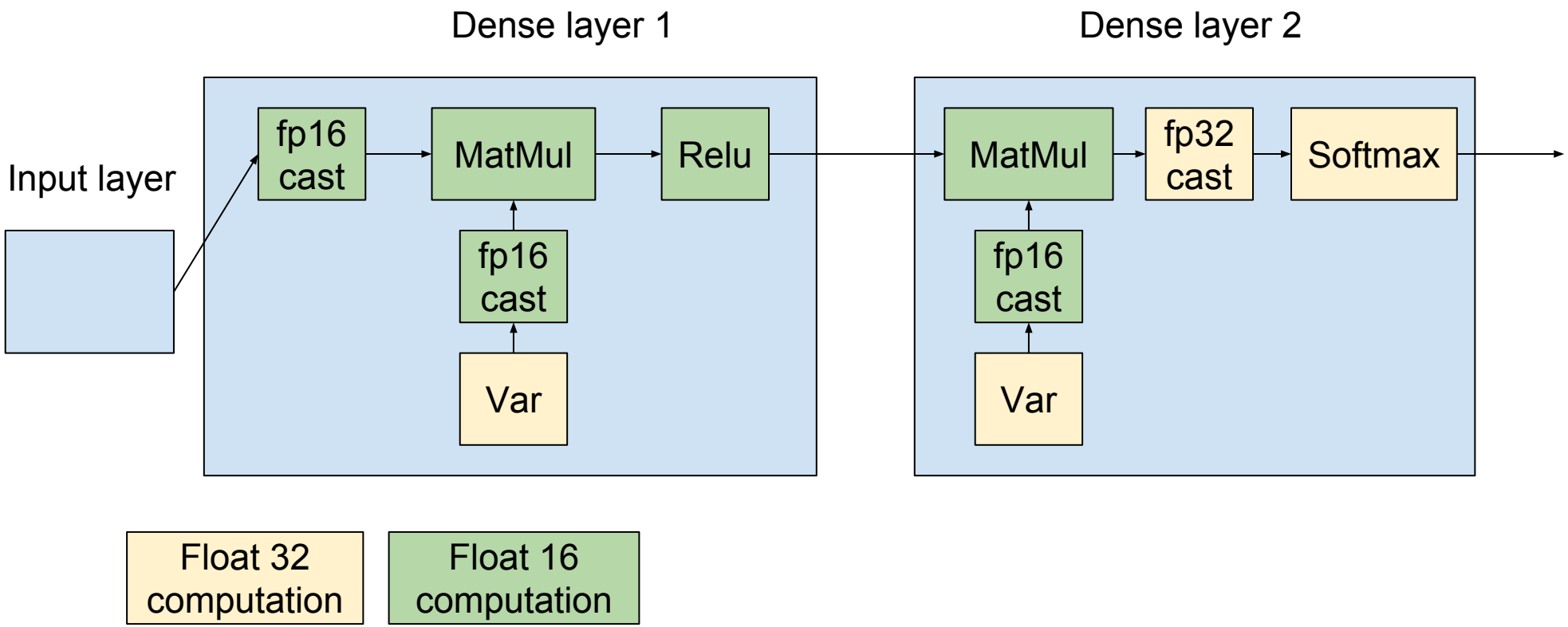
tf.keras Example

Model before mixed precision



tf.keras Example

Model after mixed precision



Passthrough Layers

For many layers, TensorFlow will infer the dtype from the input types

Cast + float16 execution may be slower than float32 execution.
If no float16 cast is needed, leave the layer in float16

```
x = tf.keras.layers.Input((), dtype='float32')
y = tf.keras.layers.Add([x, x])  # float32
z = tf.cast(y, 'float16')
w = tf.keras.layers.Add([z, z])  # float16
```

If a layer is fed inputs of different types, it will upcast the lower precision inputs

Passthrough Layers

Example

In practice, our casting decisions tend to provide near optimal performance without reducing accuracy.

```
x = tf.keras.layers.Input(())
x = tf.keras.layers.Dense(10)(x)  # Dense chooses float16
y = tf.keras.layers.Dense(10)(x)
# Add does not choose, so will infer float16 from inputs
z = tf.keras.layers.Add([x, y])
```

Add is done in float16, which is likely the right choice

Note, if the second line was removed, Add would be done in float32 due type promotion.
This can be suboptimal, but we err on side of caution

How to Override TensorFlow's Decisions

Option 1: Pass an explicit dtype

```
tf.keras.mixed_precision.experimental.set_policy("default_mixed")

model = tf.keras.layers.Sequential()
model.add(tf.keras.layers.Dense(32, activation="relu",
                                dtype="float32"))
model.add(tf.keras.layers.Dense(32, activation="softmax"))
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

How to Override TensorFlow's Decisions

Option 2: Set the policy

```
tf.keras.mixed_precision.experimental.set_policy("default_mixed")

model = tf.keras.layers.Sequential()
tf.keras.mixed_precision.experimental.set_policy("float32")
add_many_layers(model)
tf.keras.mixed_precision.experimental.set_policy("default_mixed")
model.add(tf.keras.layers.Dense(32, activation="softmax"))
model.compile(optimizer="rmsprop",
              loss="categorical_crossentropy",
              metrics=["accuracy"])
```

User Defined Layers

- If you write a layer, you can adjust the casting behaviour
  - Just need to override the ‘cast_inputs’ method of a layer
- For example, to define a layer that is done in float16 when mixed precision is enabled

```
def cast_inputs(self, inputs):
  return self._mixed_precision_policy.cast_to_lowest(inputs)
```

- Variables will be created in float32 and automatically cast to float16 as needed

User Defined Layers

Full Example

```
class CustomBiasLayer(tf.keras.layers.Layer):
  def build(self, _):
    self.v = self.add_weight('v', ())
    self.built = True

  def call(self, inputs)
    return inputs + self.v

  def cast_inputs(self, inputs):
    # Casts to float16, the policy's lowest-precision dtype
    return self._mixed_precision_policy.cast_to_lowest(inputs)
```

Automatic Loss Scaling

- tf.keras API will automatically enable dynamic loss scaling
  - Loss scale will be doubled every 2000 steps
  - Loss scale will half if any NaNs or Infs are found in the gradients
- Can optionally customize loss scaling behavior:

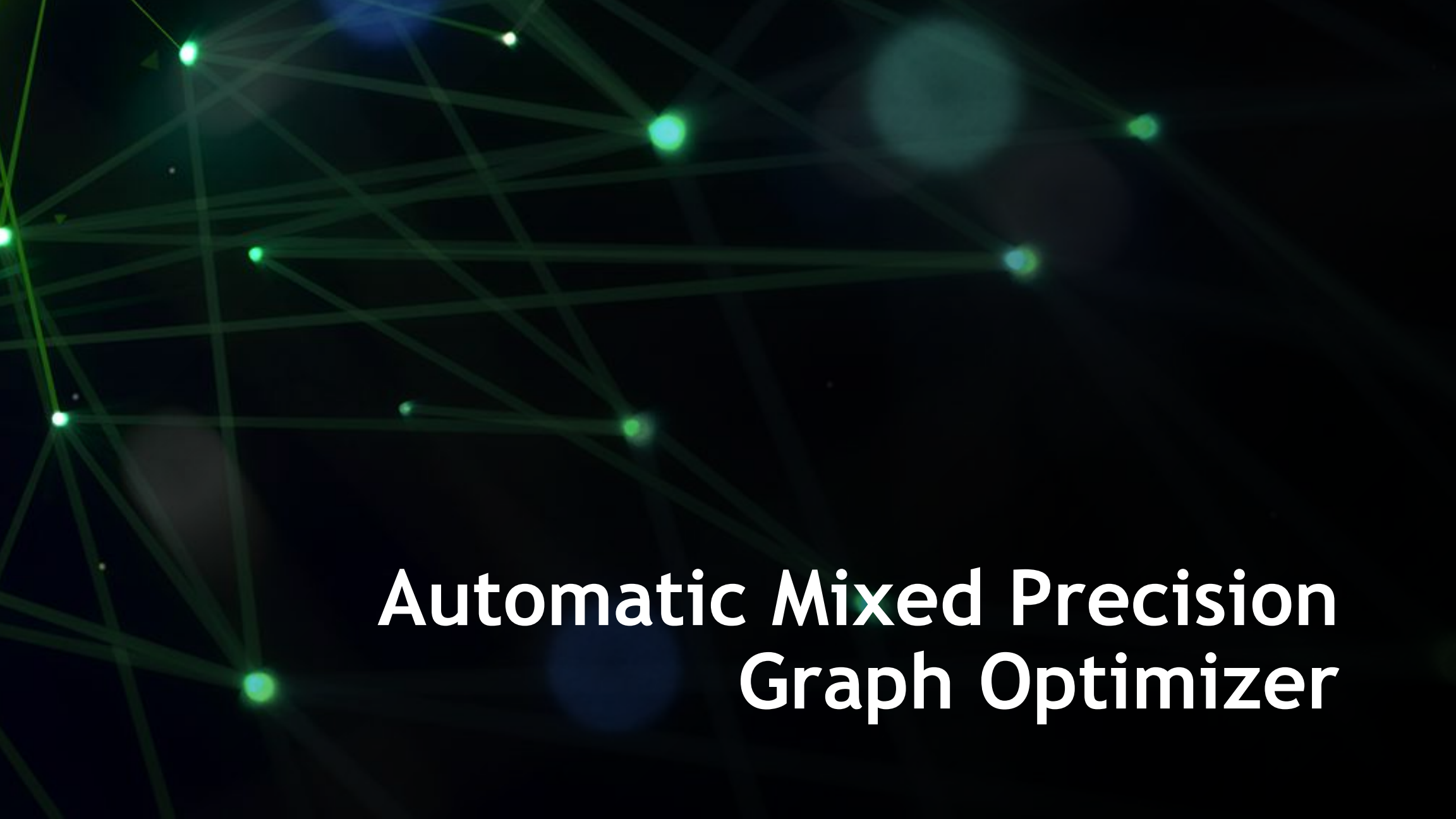
```
# Fixed loss scale of 128
policy = tf.keras.mixed_precision.Policy("default_mixed", loss_scale=128)
tf.keras.mixed_precision.experimental.set_policy(policy)
```

```
# Dynamic loss scaling, tripling the loss scale every 1000 steps
params = tf.keras.mixed_precision.DynamicLossScaleParamaters(
    incr_every_n_steps=1000, loss_scale_multiplier=3)
policy = tf.keras.mixed_precision.Policy("default_mixed", loss_scale=params)
tf.keras.mixed_precision.experimental.set_policy(policy)
```

tf.keras API Roadmap

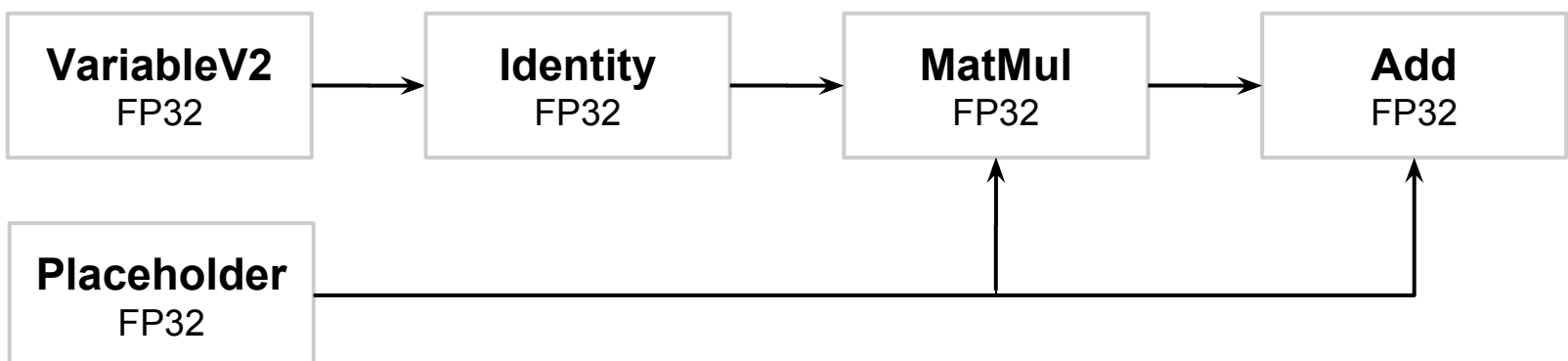
- Basic functionality (available in nightly builds)
  - Variables created in float32 and automatically cast to required dtype
  - User must cast model inputs to float16 and outputs to float32
  - User must explicitly wrap optimizer to enable loss scaling

- In upcoming months, the final API will require just one line
  - `tf.keras.mixed_precision.experimental.set_policy("default_mixed")`
  - Will have public RFC in tensorflow/community GitHub repo -- feel free to comment
  - Final API may be slightly different than what was described here

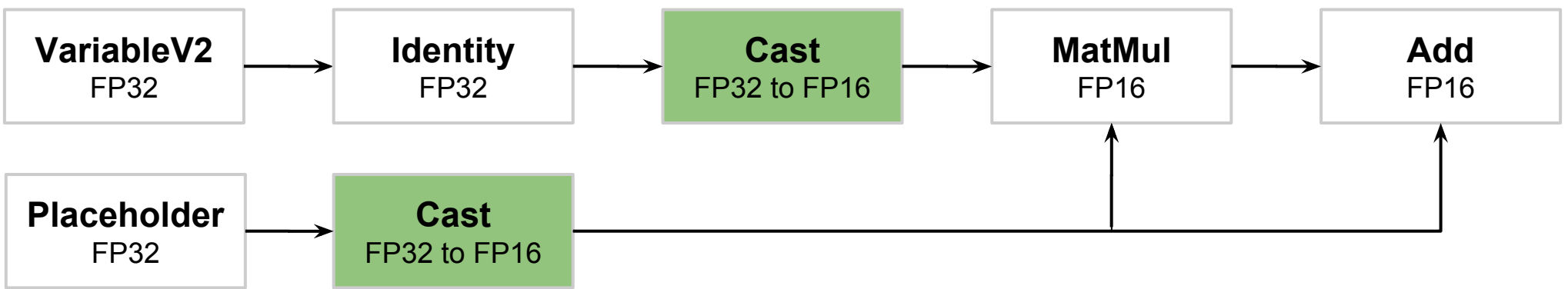

Automatic Mixed Precision
Graph Optimizer

TensorFlow Graphs

```
x = tf.placeholder(tf.float32, shape=(1024, 1024))
w = tf.get_variable('w', shape=(1024, 1024))
z = tf.add(x, tf.matmul(x, w))
```



Transformed Graphs



Enabling AMP Graph Pass

Preview Feature in NGC 19.03 TensorFlow Container

Designed to work with existing float32 models with minimal changes.

If your training script uses a `tf.train.Optimizer` to compute and apply gradients

Both Loss Scaling and mixed precision graph conversion can be enabled with a single env var.

```
export TF_ENABLE_AUTO_MIXED_PRECISION=1
python training_script.py
```

If your model does not use a `tf.train.Optimizer`, then

You must add loss scaling manually to your model

Then enable the grappler pass as follows

```
export TF_ENABLE_AUTO_MIXED_PRECISION_GRAPH_REWRITE=1
python training_script.py
```

Enabling AMP Graph Pass

Coming Soon ...

Preview implementation

- Does not work with Distribution Strategies
- Provides a single hard-coded loss scaling implementation

A more complete and flexible implementation is being upstreamed now.

```
opt = tf.train.GradientDescentOptimizer(0.001)
opt = tf.mixed_precision.experimental.mixed_precision_optimizer(opt, 1000.)
```

This enables both loss scaling and mixed precision graph optimizer.

Choosing What to Cast

Guiding Principles

1. Use float16 as much as possible, particularly for ops that can run on Tensor Cores

2. Use float32 where needed to maintain full accuracy (e.g., master weights and loss functions)

3. Minimize “cast thrashing” between float16 and float32

Choosing What to Cast

Categorize Ops into 3+1 Categories

Always Cast: Ops highly accelerated by float16. These always justify performance costs of casting inputs. Examples: `MatMul` and `Conv2d`.

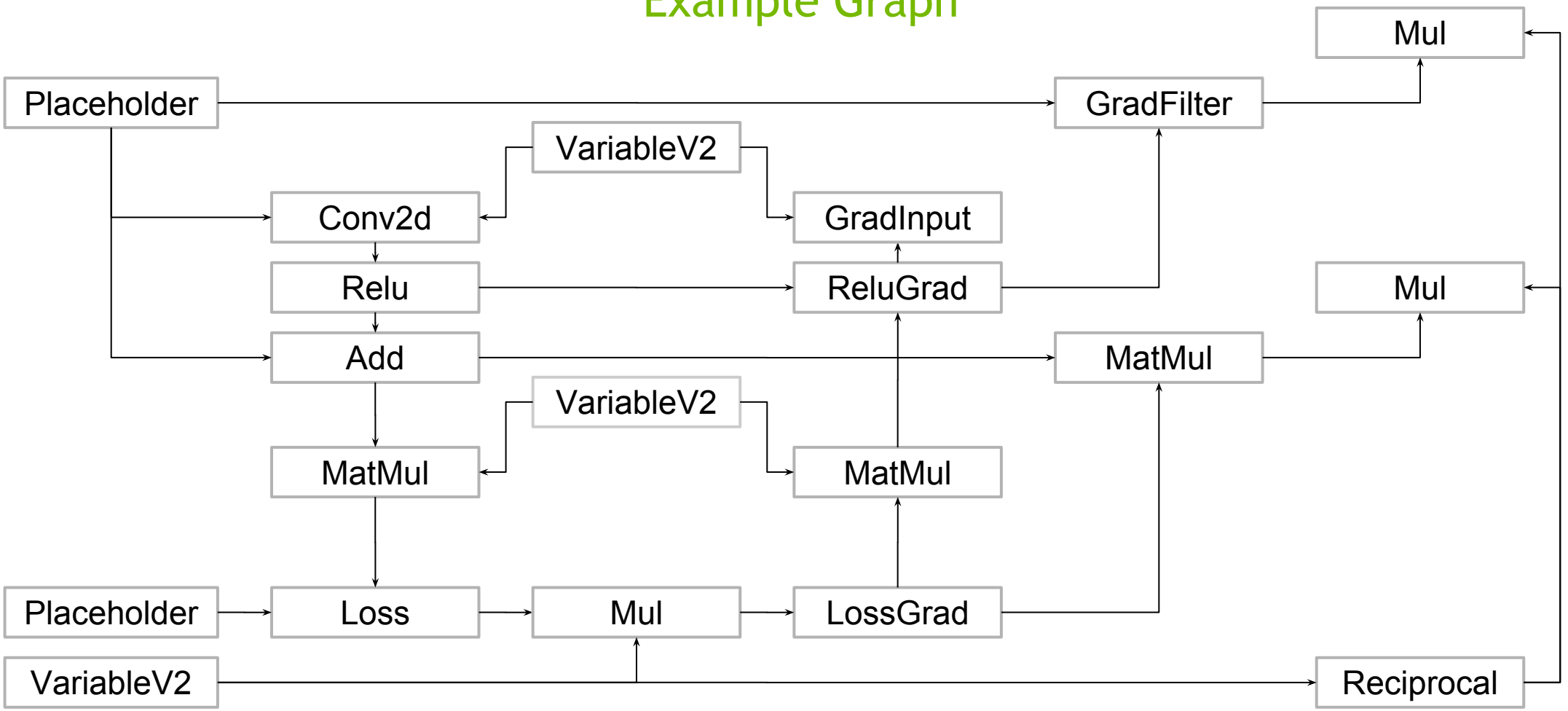
Maybe Cast: Ops available for float16 execution but not accelerated sufficiently to justify casting overhead on their own. Examples: `Add` and `Relu`.

Never Cast: Ops requiring float32 evaluation in order to maintain numerical stability. Examples: `Exp` and `SoftmaxCrossEntropyWithLogits`.

Everything Else: Ops lacking float16 implementations or operating on non-floating point inputs.

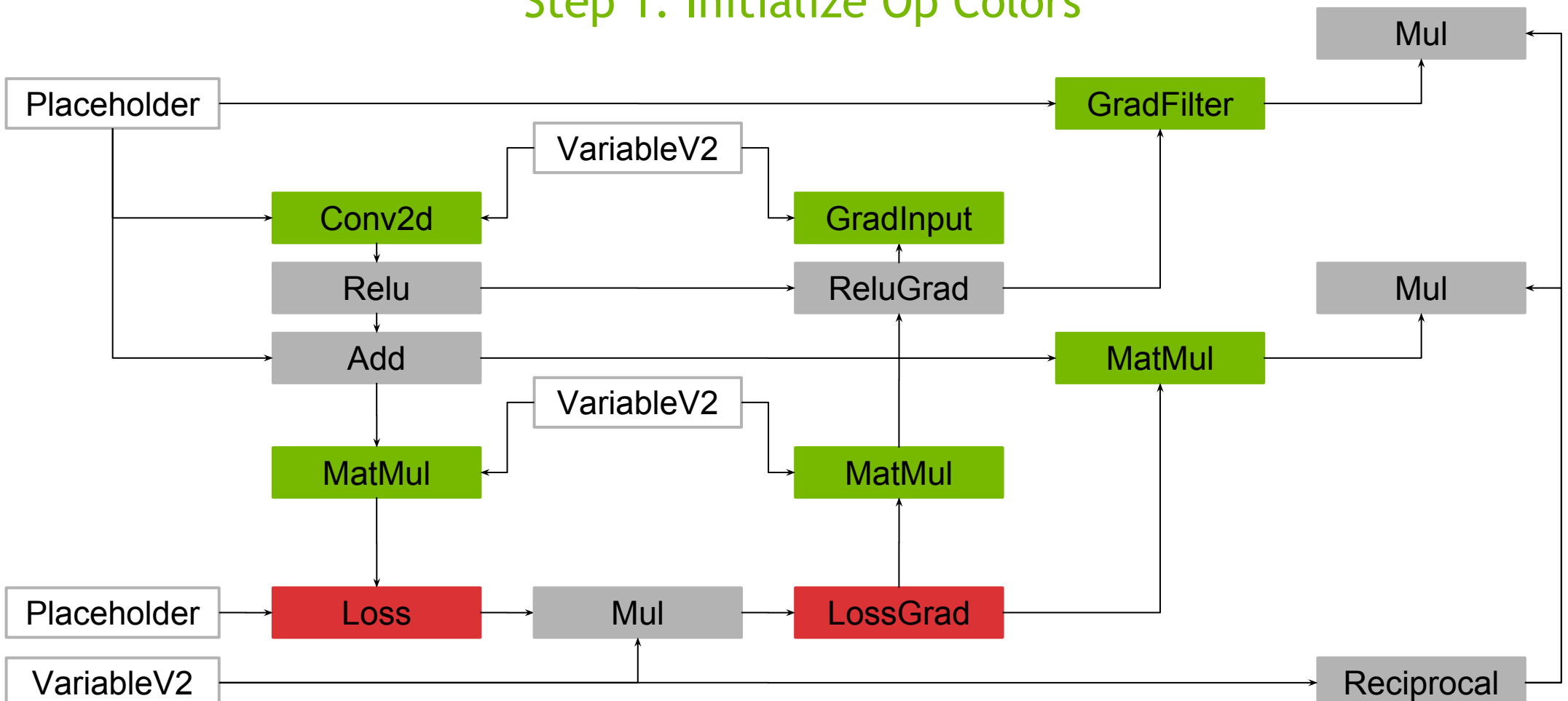
Graph Coloring Example

Example Graph



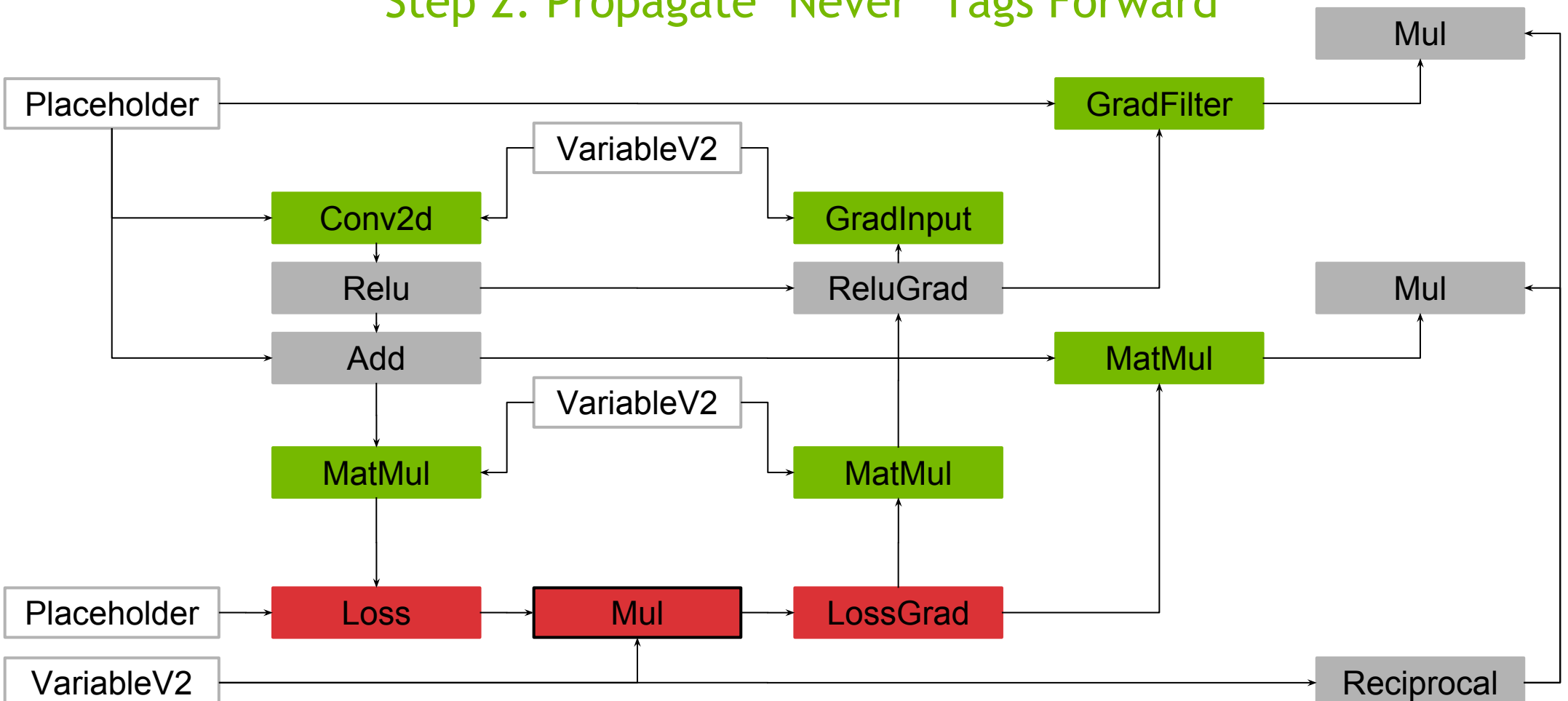
Graph Coloring Example

Step 1: Initialize Op Colors



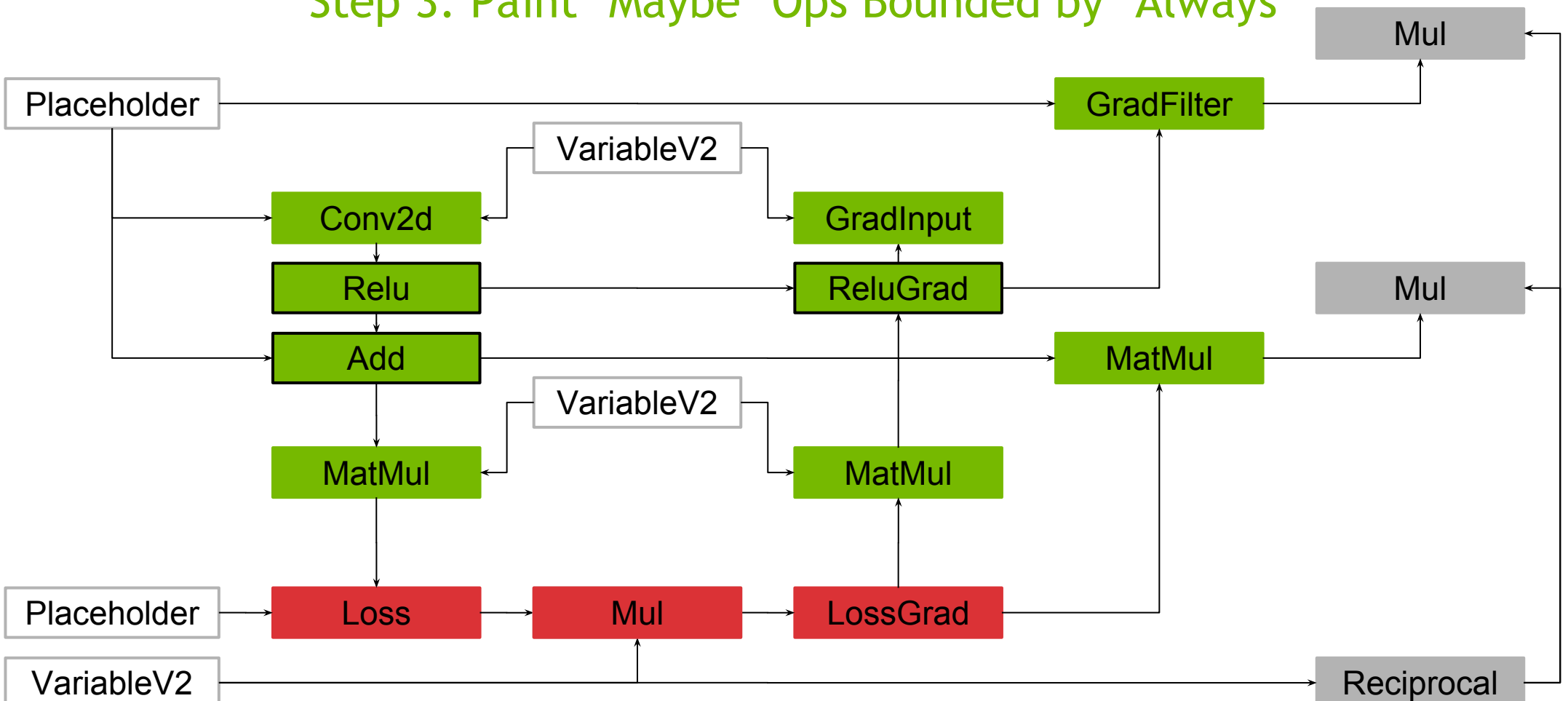
Graph Coloring Exmple

Step 2: Propagate ‘Never’ Tags Forward



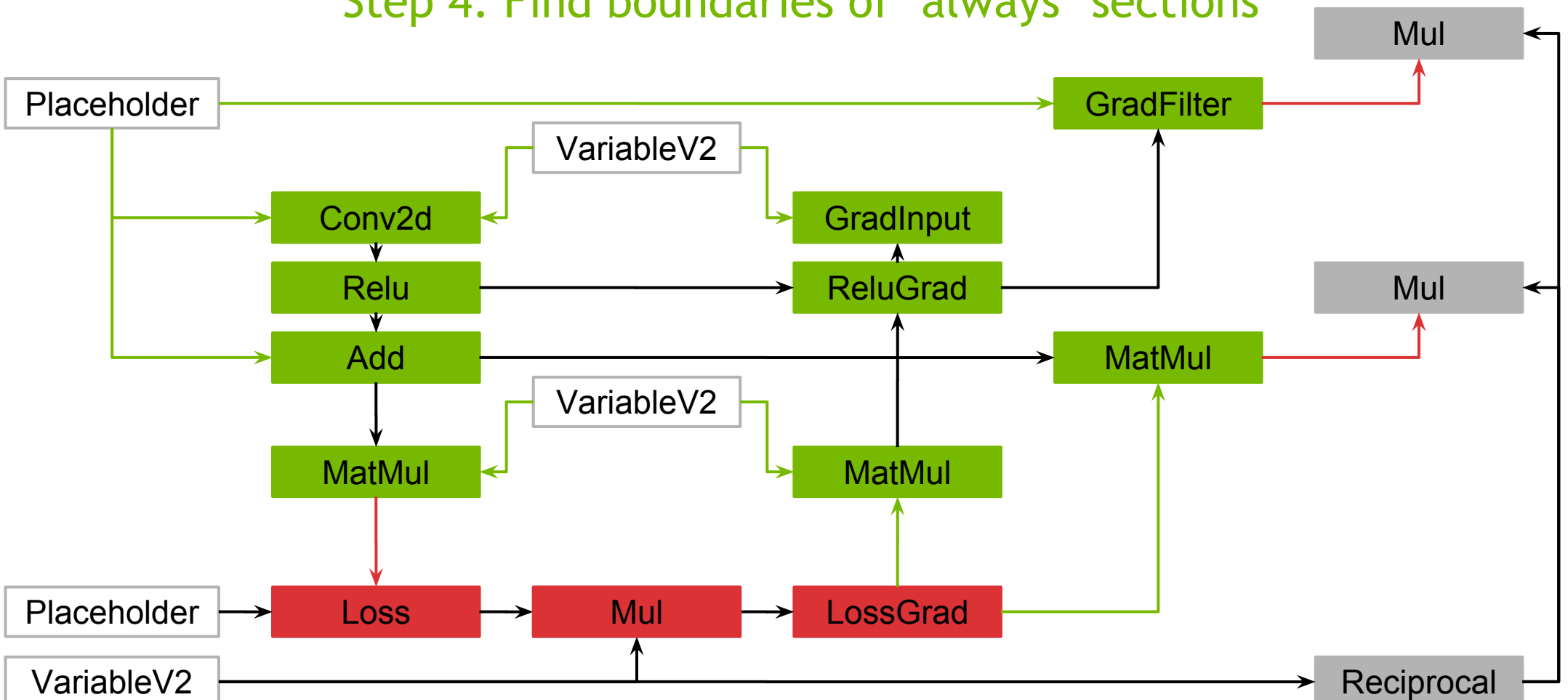
Graph Coloring Exmple

Step 3: Paint ‘Maybe’ Ops Bounded by ‘Always’



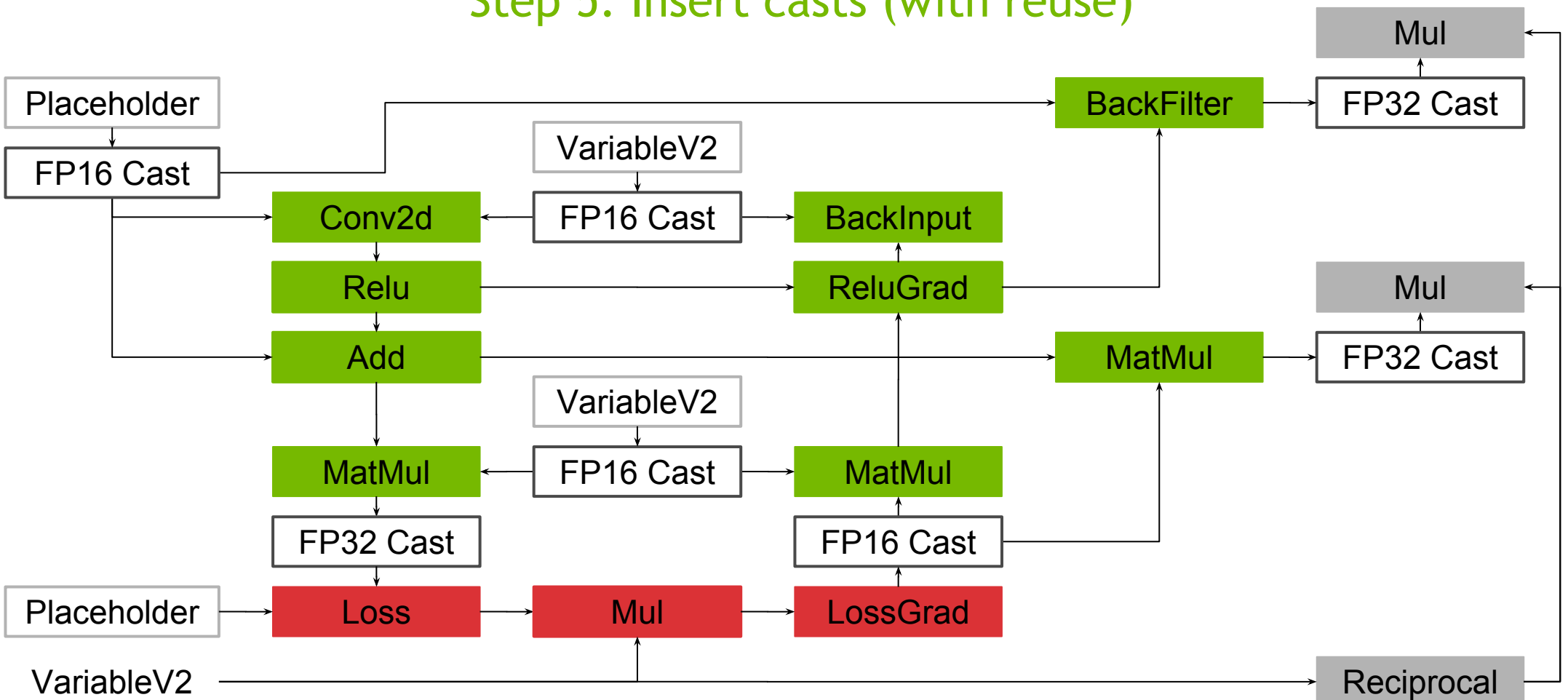
Graph Coloring Exmple

Step 4: Find boundaries of ‘always’ sections



Graph Coloring Exmple

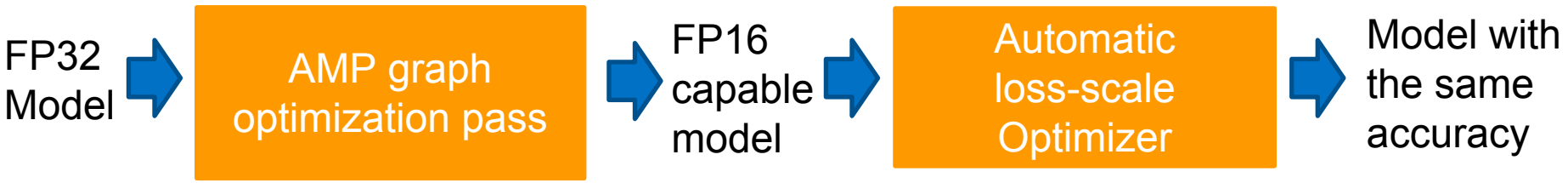
Step 5: Insert casts (with reuse)



Results

AMP LARGELY DEPLOYED INTO ALIBABA PAI PLATFORM

AMP + Automatic Loss Scaling Optimizer



- No laborious FP32/FP16 casting work anymore
- Already supporting diversified internal workloads: NLP/CNN/BERT/Sparse Embedding/…
- **1.3~3X** time-to-accuracy speed-up
- Collaboratively work with NVIDIA to push into TF community

Alibaba Group
阿里巴巴集团

AMP LARGELY DEPLOYED INTO ALIBABA PAI PLATFORM

More than 10,000 training jobs have benefited from AMP over last half a year.

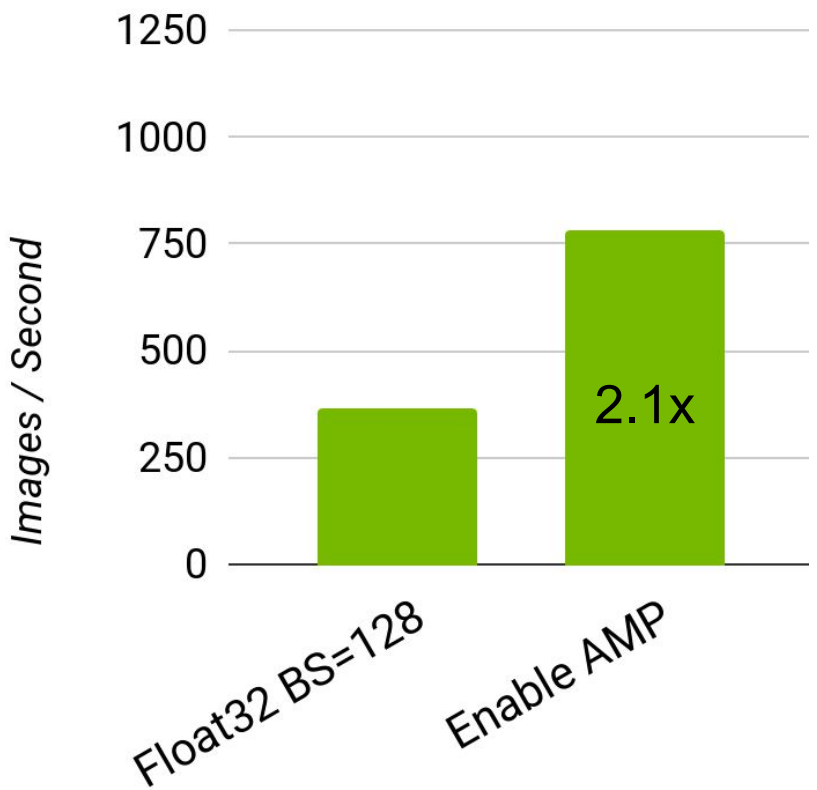
Model Class	Details	Speedup
DNN	Data Mining/Content Mining	2.4-2.9X
CNN	Image Understanding/Image Recognition/Video Recommendation	1.4-1.5X
Transformer	NLP	1.5X
BERT	NLP/Knowledge Graph	1.5-1.6X

GPU: 1x V100-SXM2-16GB | CPU: Xeon Platinum 8163
TensorFlow: 1.8, FP32 w/o AMP vs FP16 using AMP, batch size stayed the same

Alibaba Group
阿里巴巴集团

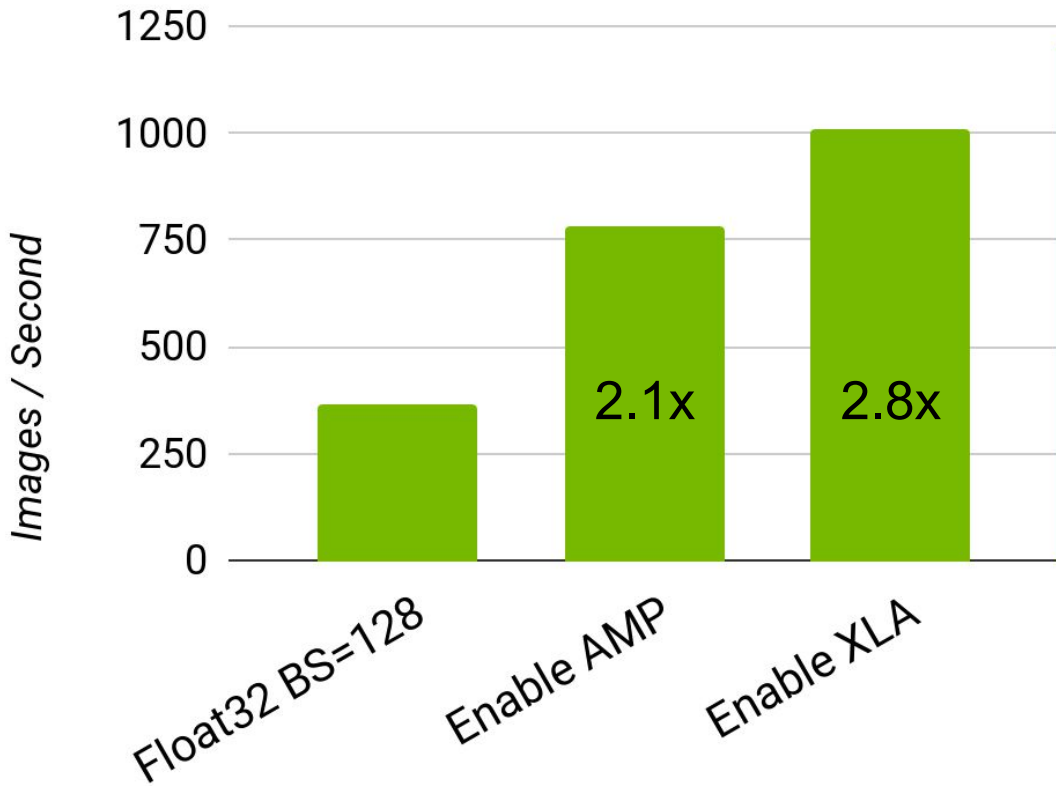
ResNet50 v1.5

Training on a single V100



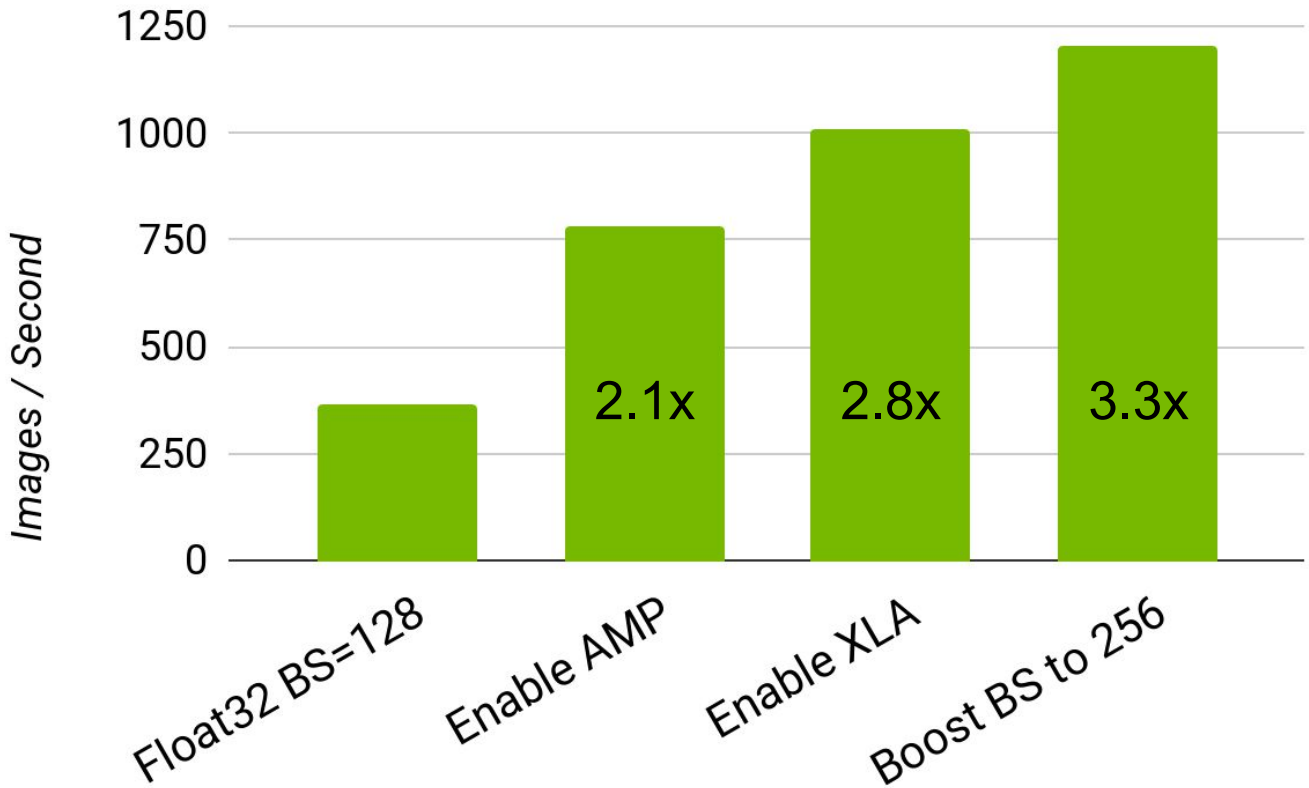
ResNet50 v1.5

Training on a single V100



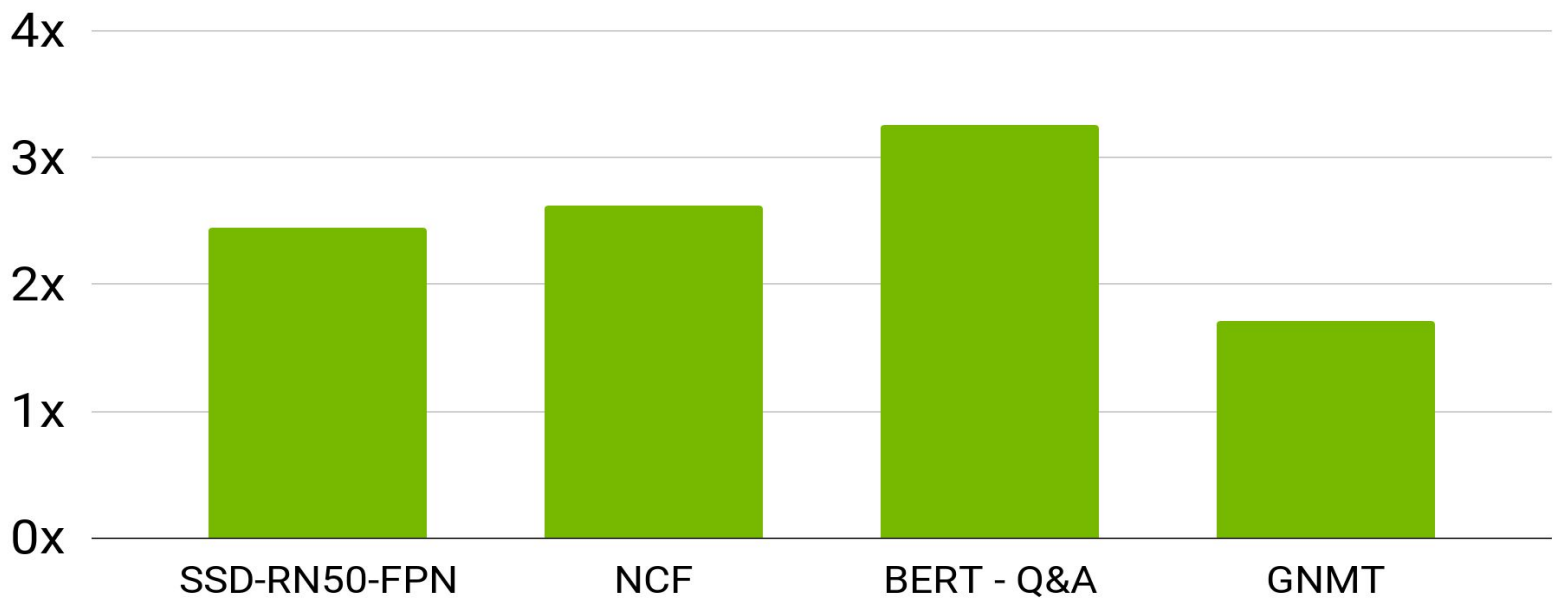
ResNet50 v1.5

Training on a single V100



Additional Results

V100 Training Speedups



https://devblogs.nvidia.com/nvidia-automatic-mixed-precision-tensorflow/

AMP Resources

NVIDIA NGC 19.03 TensorFlow Container
https://ngc.nvidia.com/catalog/containers/nvidia:tensorflow

Example Models
https://github.com/NVIDIA/DeepLearningExamples/tree/master/TensorFlow/

AMP Graph Optimizer PR
https://github.com/tensorflow/tensorflow/pull/26342


NVIDIA