S8906: FAST DATA PIPELINES FOR DEEP LEARNING TRAINING

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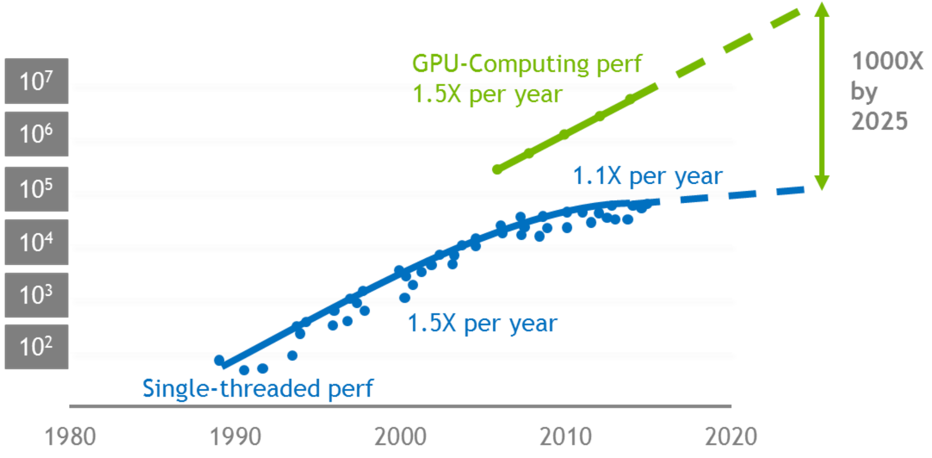
THE PROBLEM

CPU BOTTLENECK OF DL TRAINING

CPU : GPU ratio

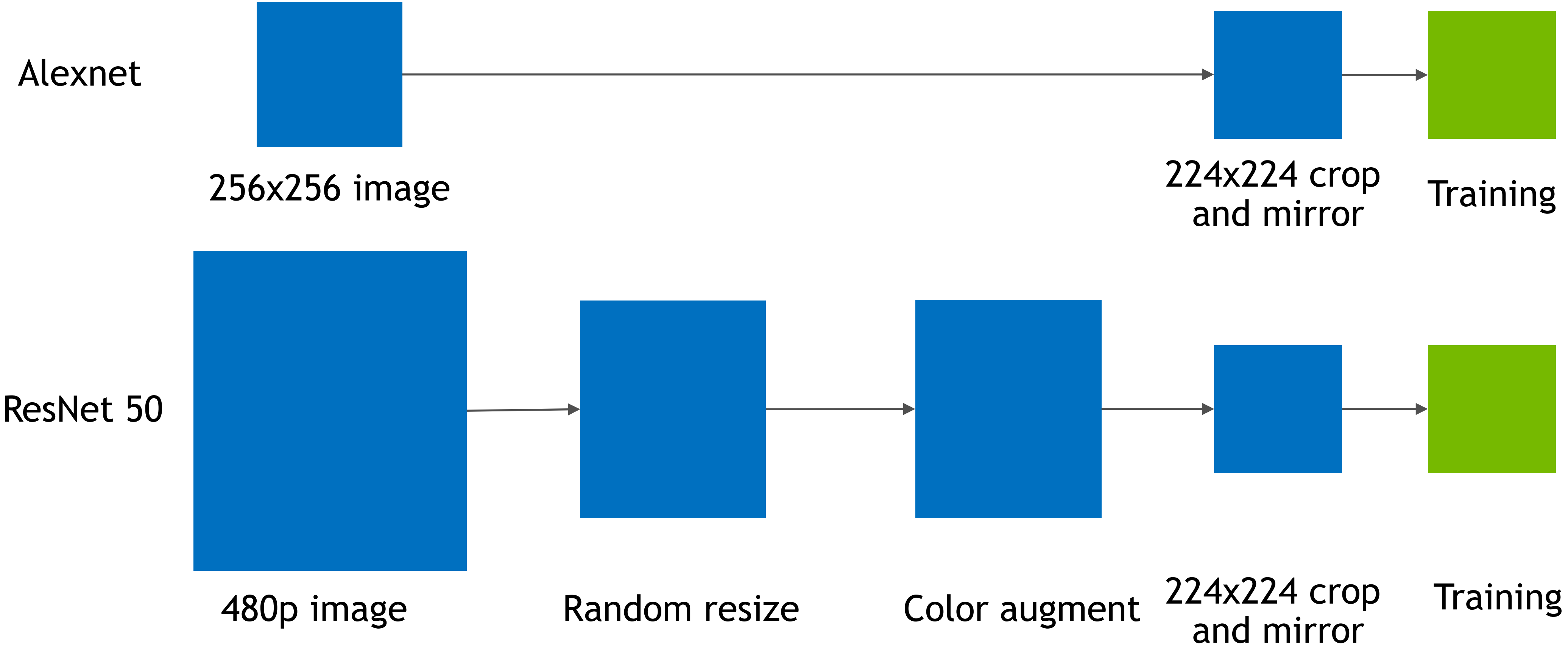
- Multi-GPU, dense systems are more common (DGX-1V, DGX-2)
- Using more cores / sockets is very expensive
- CPU to GPU ratio becomes lower:
  - DGX-1V: **40 cores / 8, 5 cores / GPU**
  - DGX-2: **48 cores / 16, 3 cores / GPU**



Original data up to the year 2010 collected and plotted by M. Horowitz, F. Labonte, O. Shacham, K. Olukotun, L. Hammond, and C. Batten New plot and data collected for 2010-2015 by K. Rupp

CPU BOTTLENECK OF DL TRAINING

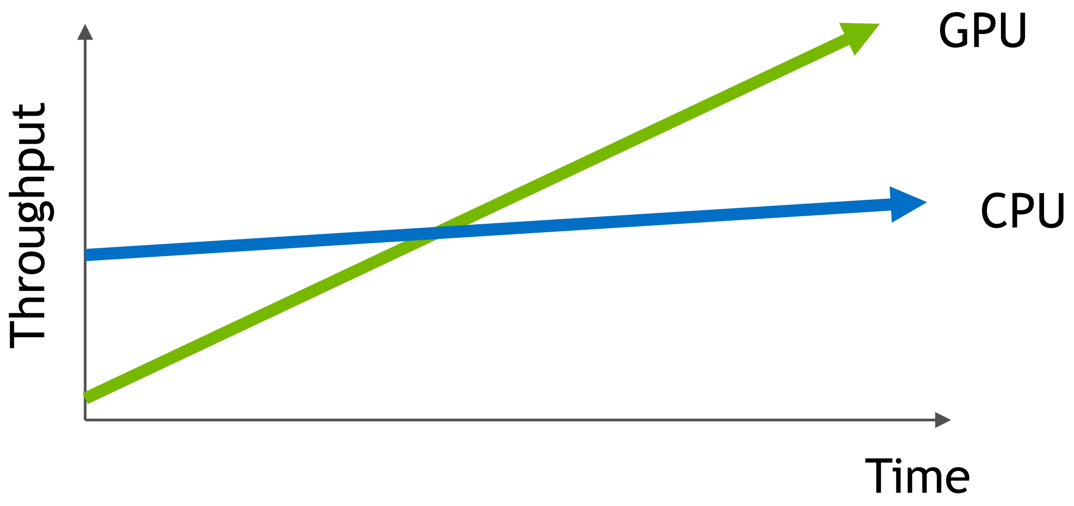
Complexity of I/O pipeline



CPU BOTTLENECK OF DL TRAINING

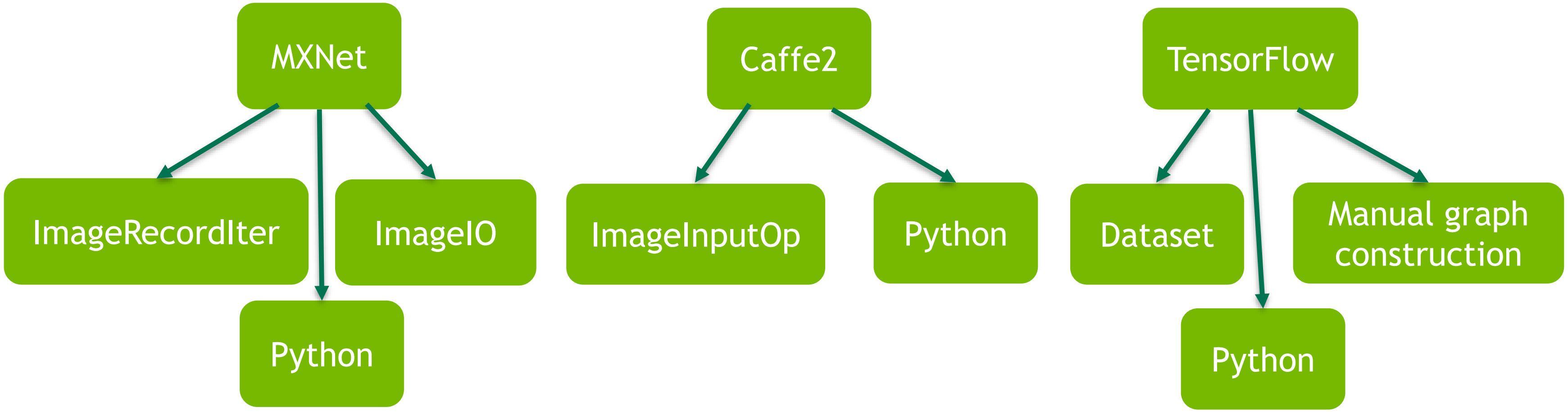
Increased complexity of CPU-based I/O pipeline

Higher GPU to CPU ratio



LOTS OF FRAMEWORKS

Lots of effort



Frameworks have their own I/O pipelines (often more than 1!)

Lots of duplicated effort to optimize them all

Training process is not portable even if the model is (e.g. via ONNX)

LOTS OF FRAMEWORKS

Lots of effort

Optimized I/O pipelines are not flexible and often unsuitable for research

```
train = mx.io.ImageRecordIter(
        path_imgrec         = args.data_train,
        path_imgidx         = args.data_train_idx,
        label_width         = 1,
        mean_r              = rgb_mean[0],
        mean_g              = rgb_mean[1],
        mean_b              = rgb_mean[2],
        data_name           = 'data',
        label_name          = 'softmax_label',
        data_shape          = image_shape,
        batch_size          = 128,
        rand_crop           = True,
        max_random_scale    = 1,
        pad                 = 0,
        fill_value          = 127,
        min_random_scale    = 0.533,
        max_aspect_ratio    = args.max_random_aspect_ratio,
        random_h            = args.max_random_h,
        random_s            = args.max_random_s,
        random_l            = args.max_random_l,
        max_rotate_angle    = args.max_random_rotate_angle,
        max_shear_ratio     = args.max_random_shear_ratio,
        rand_mirror         = args.random_mirror,
        preprocess_threads  = args.data_nthreads,
        shuffle             = True,
        num_parts           = 0,
        part_index          = 1)
```

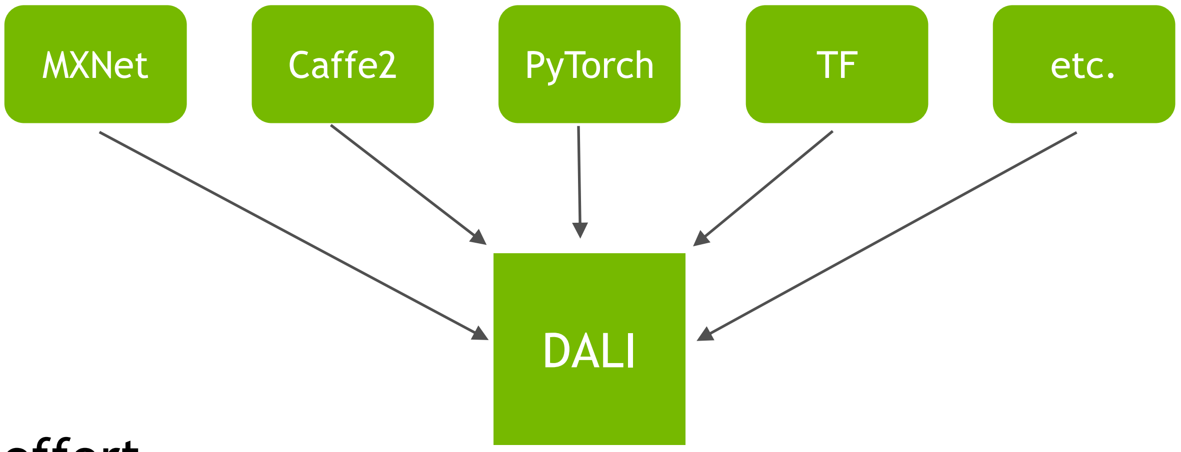
vs

```
image, _ = mx.image.random_size_crop(image,
(data_shape, data_shape), 0.08, (3/4., 4/3.))
image = mx.nd.image.random_flip_left_right(image)
image = mx.nd.image.to_tensor(image)
image = mx.nd.image.normalize(image, mean=(0.485,
0.456, 0.406), std=(0.229, 0.224, 0.225))
return mx.nd.cast(image, dtype), label
```

Inflexible fast

flexible slow

SOLUTION: ONE LIBRARY

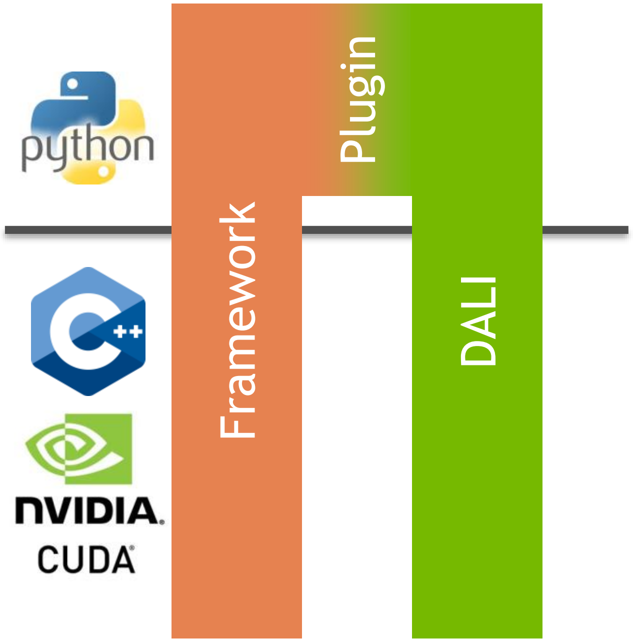


- Centralize the effort
- Integrate into all frameworks
- Provide both flexibility and performance

DALI: OVERVIEW

DALI

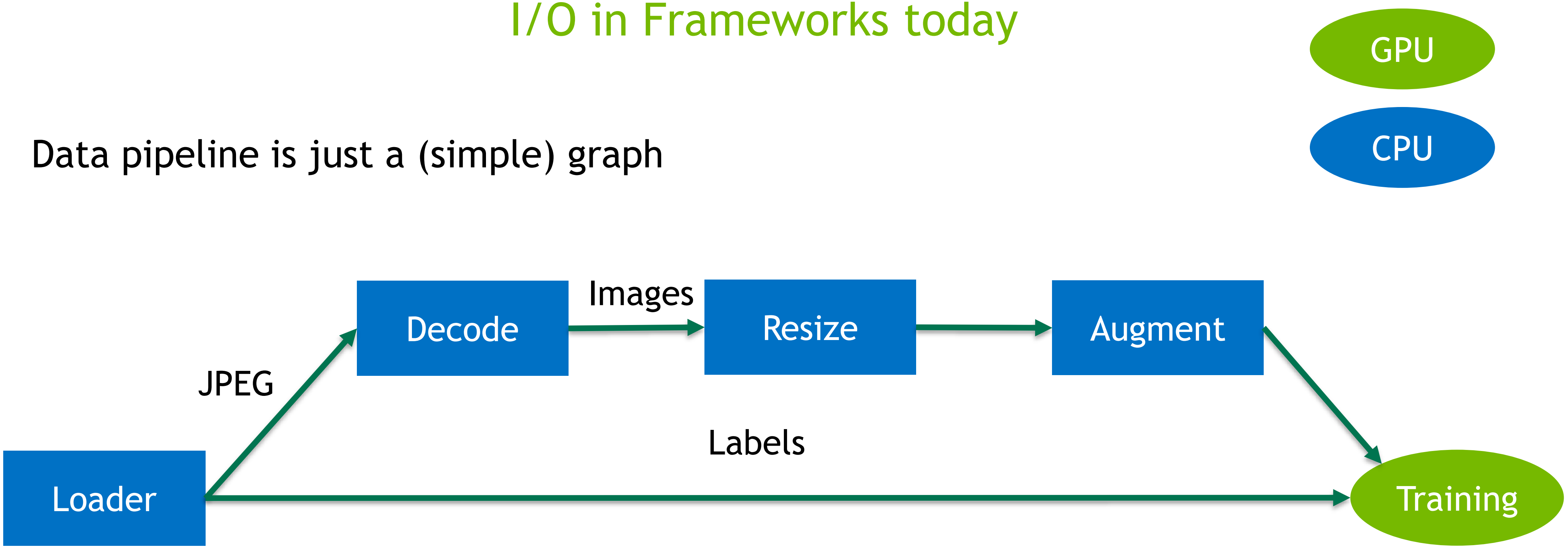
- Flexible, high-performance image data pipeline
- Python / C++ frontends with C++ / CUDA backend
- Minimal (or no) changes to the frameworks required
- Full pipeline - from disk to GPU, ready to train
- OSS (soon)



GRAPH WITHIN A GRAPH

I/O in Frameworks today

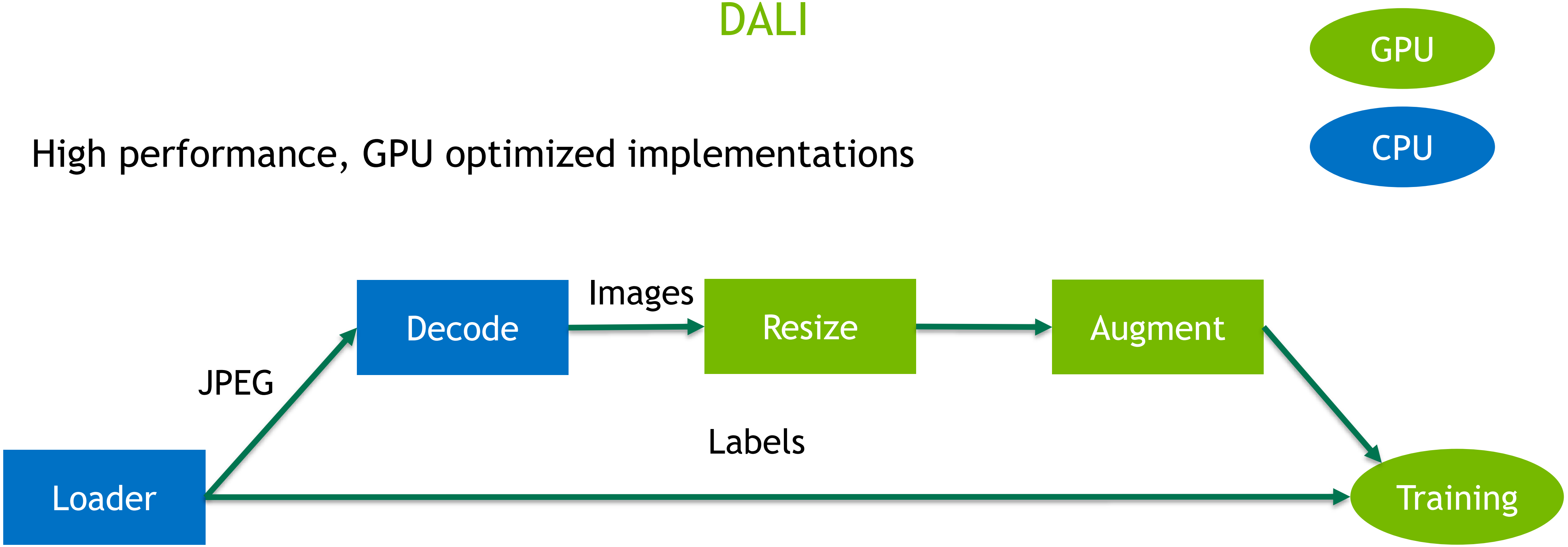
Data pipeline is just a (simple) graph



GPU OPTIMIZED PRIMITIVES

DALI

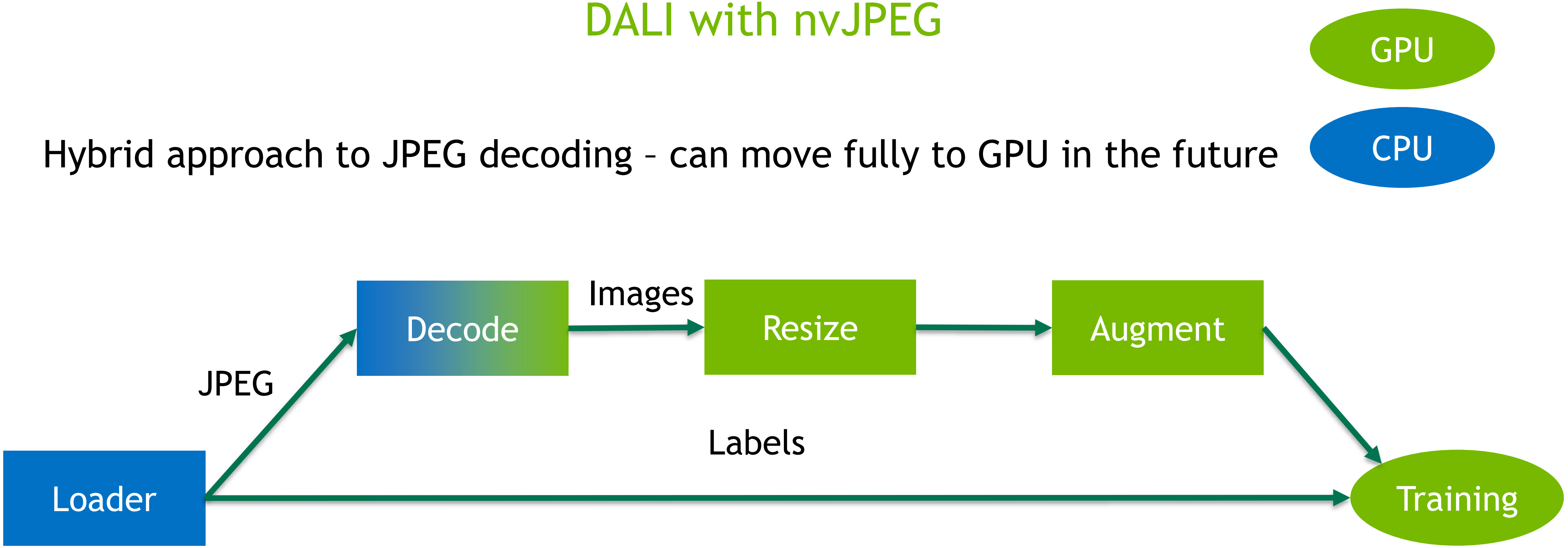
High performance, GPU optimized implementations



GPU ACCELERATED JPEG DECODE

DALI with nvJPEG

Hybrid approach to JPEG decoding – can move fully to GPU in the future



SET YOUR DATA FREE

DALI

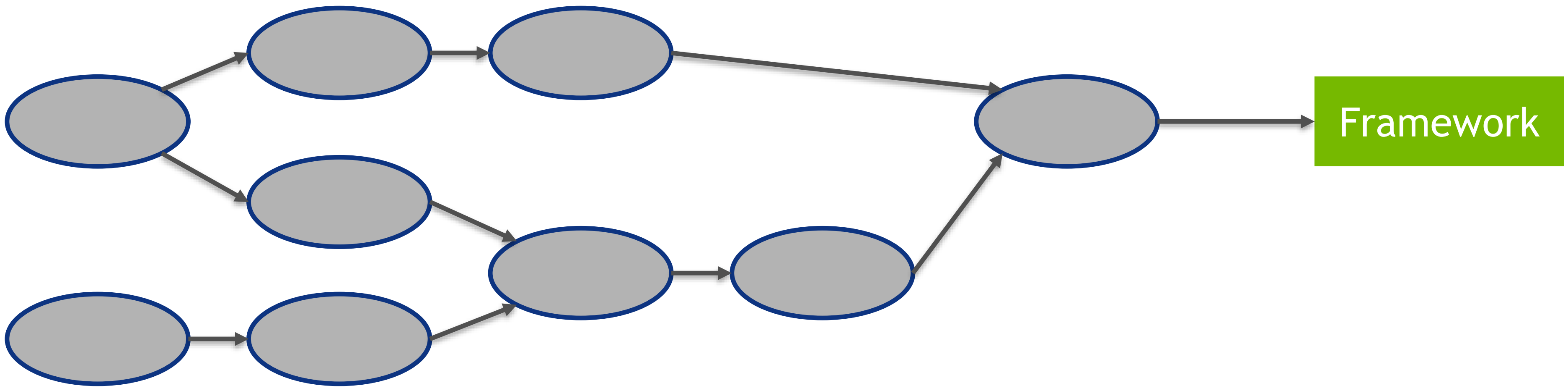
LMDB (Caffe, Caffe2)	RecordIO (MXNet)	TFRecord (TensorFlow)	List of JPEGs (PyTorch, others)

Use any file format in any framework

BEHIND THE SCENES:
PIPELINE

PIPELINE

Overview

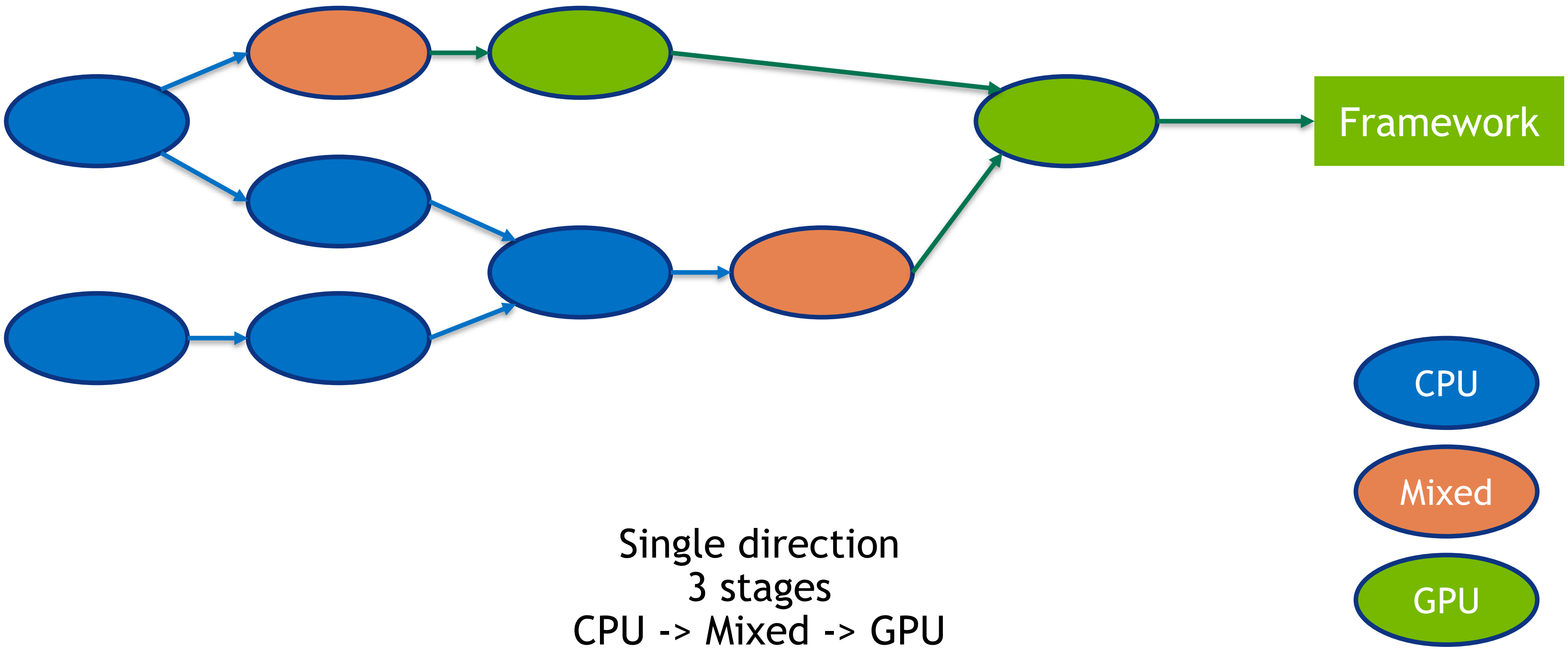


One pipeline per GPU

The same logic for multithreaded and multiprocess frameworks

PIPELINE

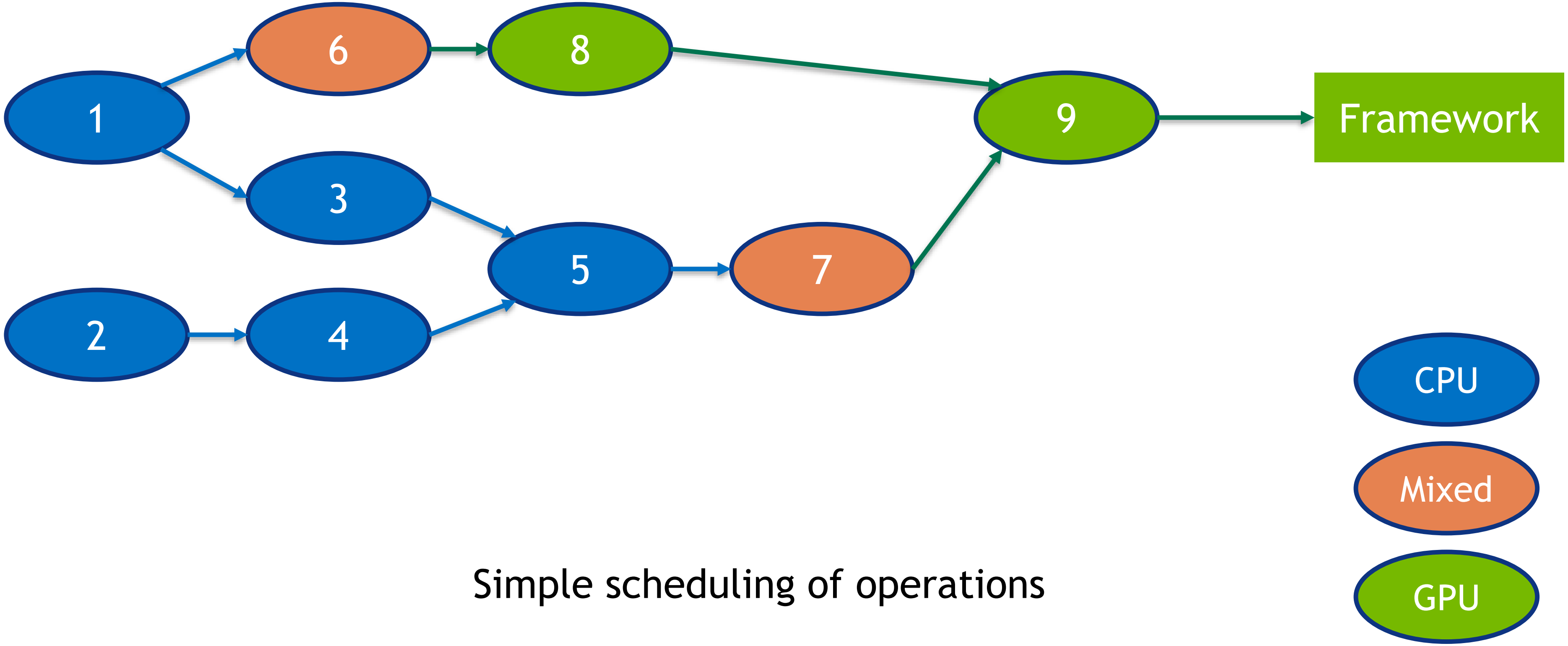
Overview



Single direction
3 stages
CPU -> Mixed -> GPU

PIPELINE

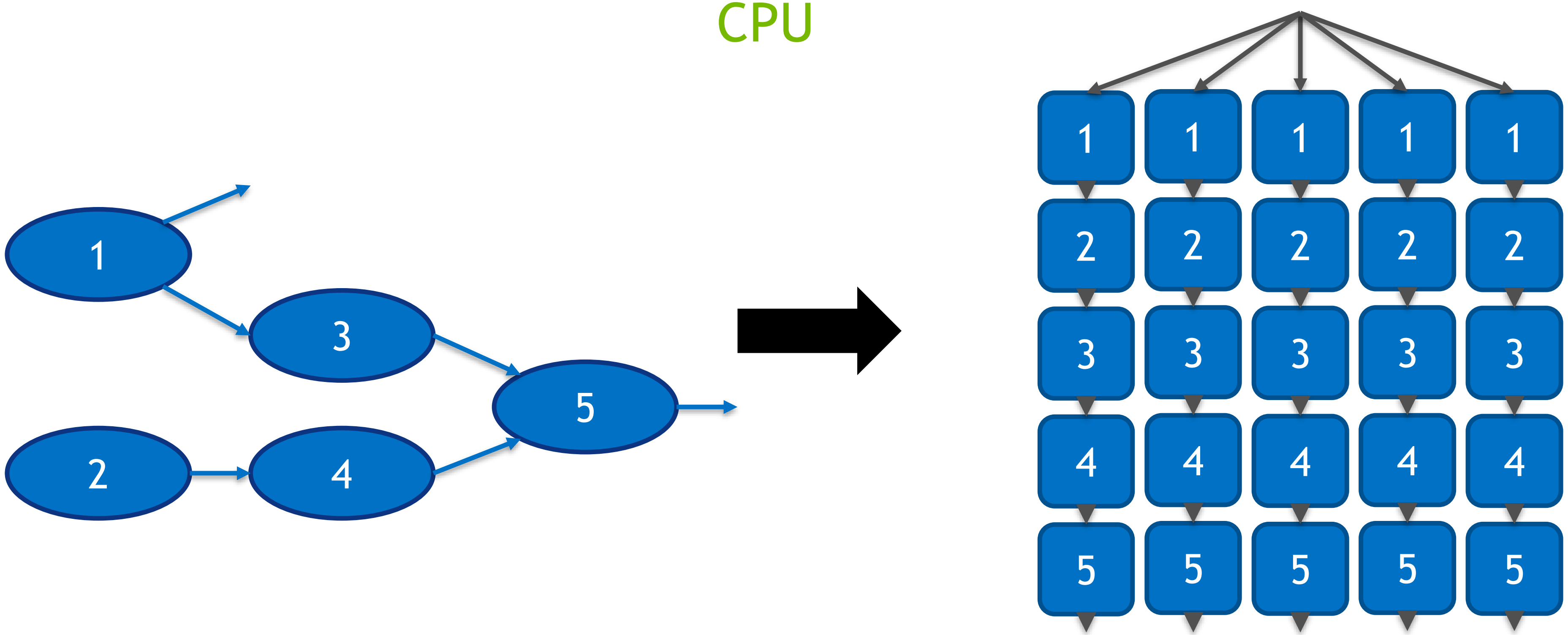
Overview



Simple scheduling of operations

PIPELINE

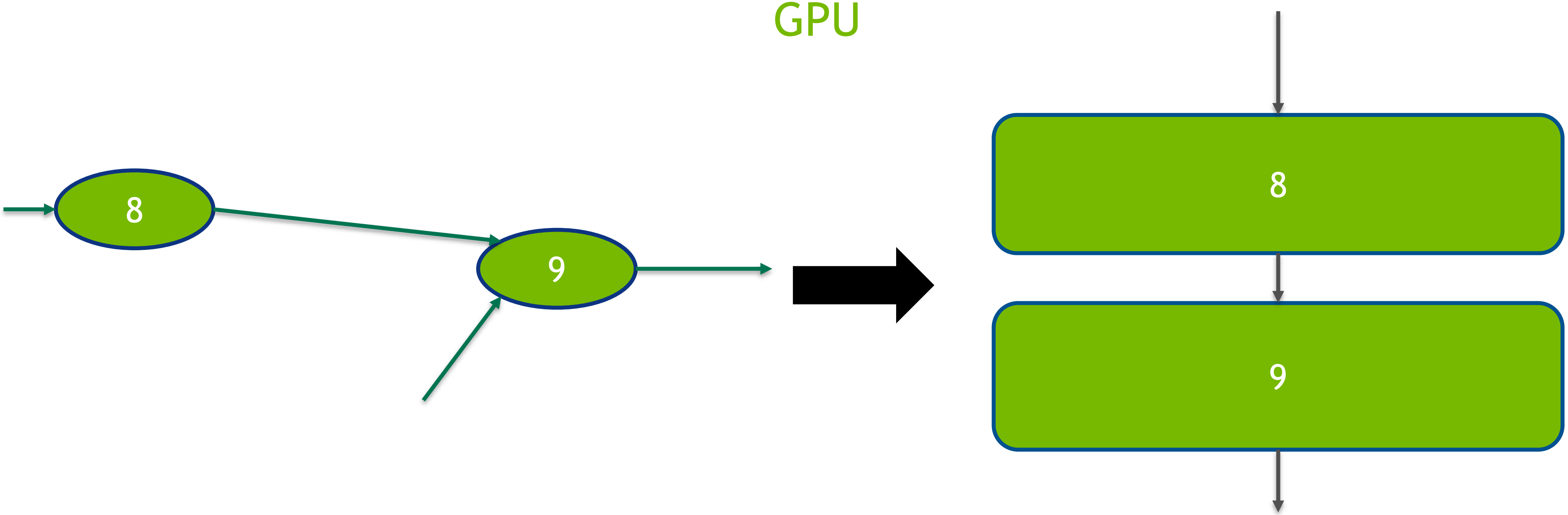
CPU



Operations processed per-sample in a thread pool

PIPELINE

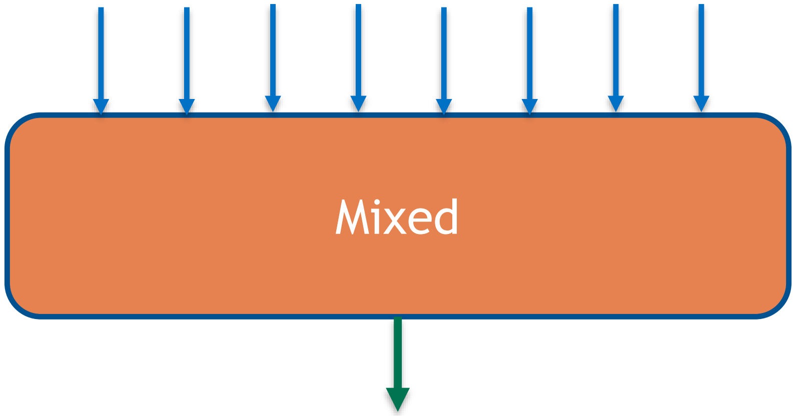
GPU



Batched processing of data

PIPELINE

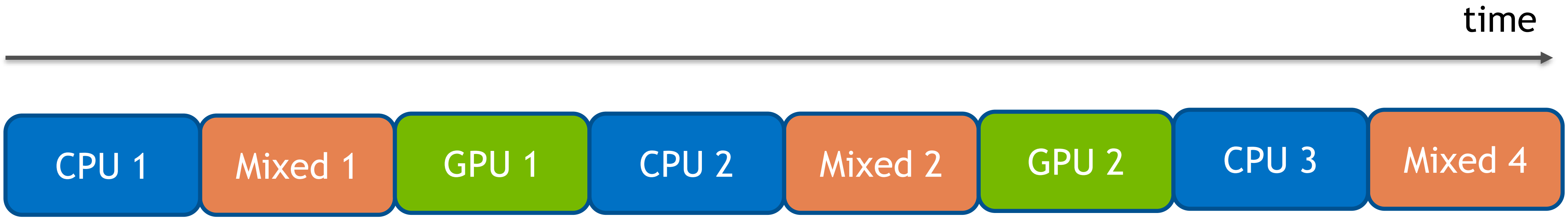
Mixed



A bridge between CPU and GPU
Per-sample input, batched output
Used also for batching CPU data (for CPU outputs of the pipeline)

EXECUTOR

Pipelining the pipeline

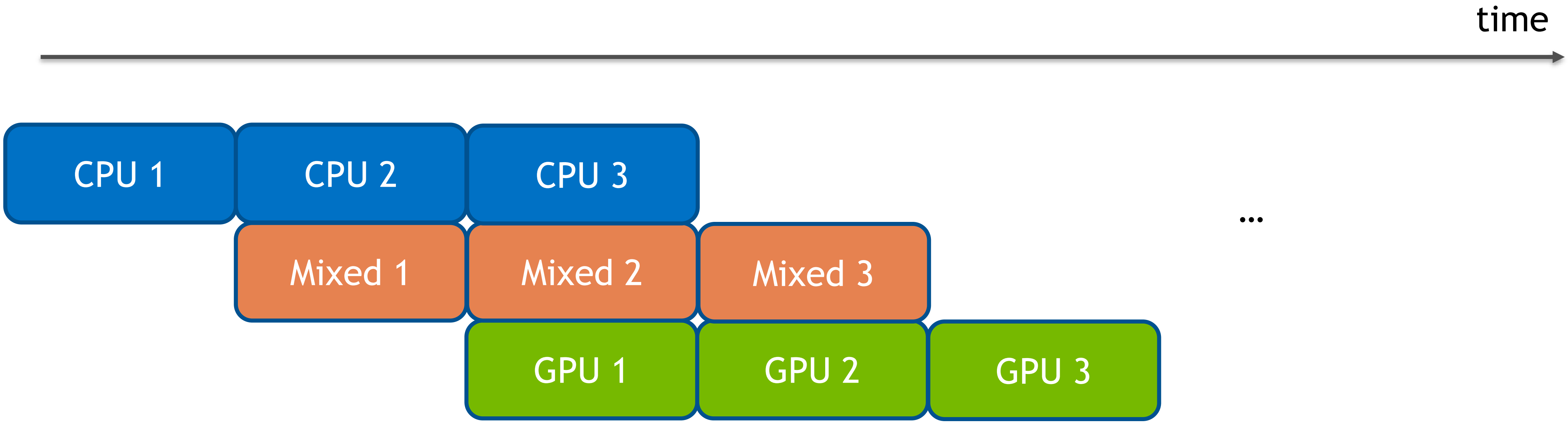


CPU, Mixed and GPU stages need to be executed serially

But each batch of data is independent…

EXECUTOR

Pipelining the pipeline

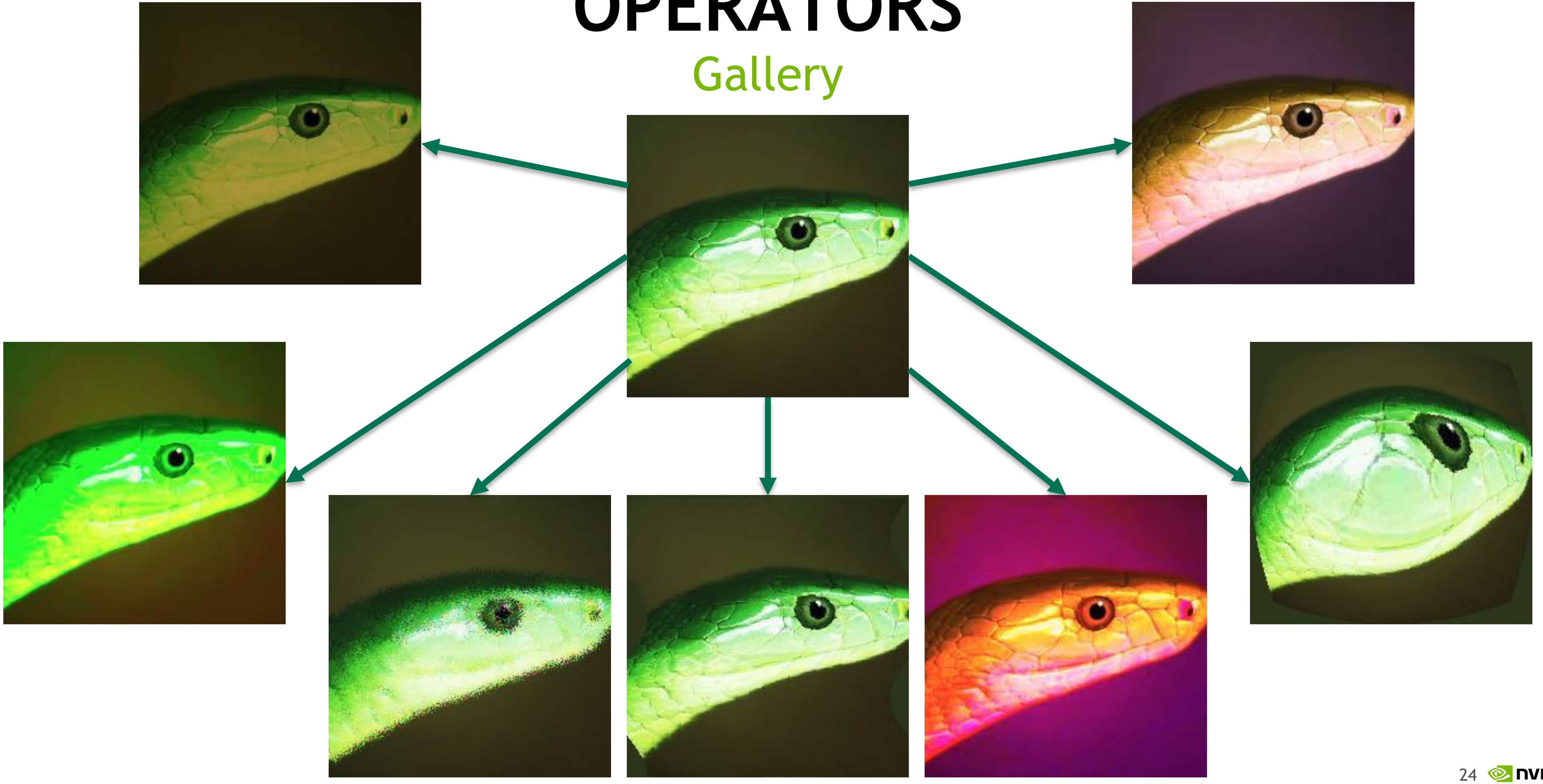


Each stage is asynchronous

Stages of given batch synchronized via events

OPERATORS

Gallery



USING DALI

EXAMPLE: RESNET-50 PIPELINE

Pipeline class

```
import dali
import dali.ops as ops

class HybridRN50Pipe(dali.Pipeline):
    def __init__(self, batch_size, num_threads, device_id, num_devices):
        super(HybridRN50Pipe, self).__init__(batch_size,
                num_threads, device_id)
        # define used operators

    def define_graph(self):
        # define graph of operations
```

EXAMPLE: RESNET-50 PIPELINE

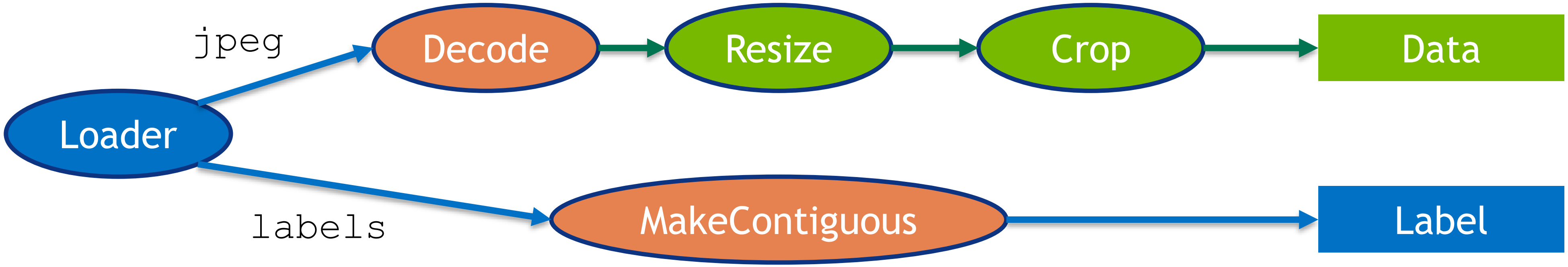
Defining operators

```python
def __init__(self, batch_size, num_threads, device_id, num_devices):
    super(HybridRN50Pipe, self).__init__(batch_size, num_threads,
                                          device_id)
    self.loader = ops.Caffe2Reader(path=lmdb_path, shard_id=dev_id,
                                   num_shards=num_devices)
    self.decode = ops.HybridDecode(output_type=dali.types.RGB)
    self.resize = ops.Resize(device="gpu", resize_a=256,
                             resize_b=480, random_resize=True,
                             image_type=types.RGB)
    self.crop = ops.CropMirrorNormalize(device="gpu",
                             random_crop=True, crop=(224, 224),
                             mirror_prob=0.5, mean=[128.,128.,128.],
                             std=[1.,1.,1.], output_layout=dali.types.NCHW)
```

EXAMPLE: RESNET-50 PIPELINE

Defining graph

```python
def define_graph(self):
    jpeg, labels = self.loader(name="Reader")
    images = self.decode(jpeg)
    resized_images = self.resize(images)
    cropped_images = self.crop(resized_images)
    return [cropped_images, labels]
```



EXAMPLE: RESNET-50 PIPELINE

Usage: MXNet

```
import mxnet as mx
from dali.plugin.mxnet import DALIIterator

pipe = HybridRN50Pipe(128, 2, 0, 1)
pipe.build()
train = DALIIterator(pipe, pipe.epoch_size("Reader"))

model.fit(train,
          # other parameters
         )
```

EXAMPLE: RESNET-50 PIPELINE

Usage: TensorFlow

```
import tensorflow as tf
from dali.plugin.tf import DALIIterator

pipe = HybridRN50Pipe(128, 2, 0, 1)
serialized_pipe = pipe.serialize()
train = DALIIterator()

with tf.session() as sess:
    images, labels = train(serialized_pipe)
    # rest of the model using images and labels
    sess.run(...)
```

EXAMPLE: RESNET-50 PIPELINE

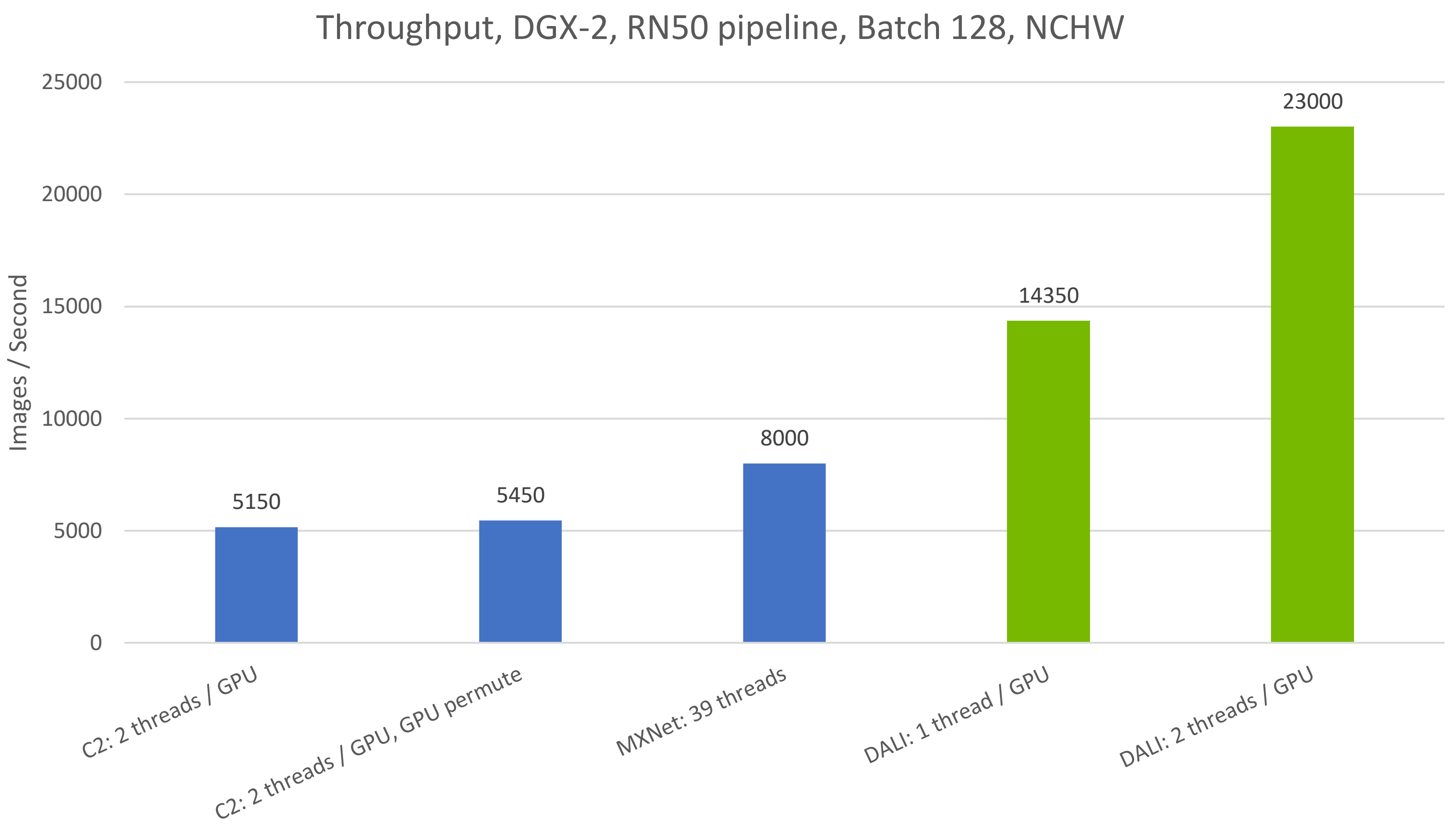
Usage: Caffe 2

```
from caffe2.python import brew

pipe = HybridRN50Pipe(128, 2, 0, 1)
serialized_pipe = pipe.serialize()

data, label = brew.dali_input(model, ["data", "label"],
                              serialized_pipe=serialized_pipe)

# Add the rest of your network as normal
conv1 = brew.conv(model, data, “conv1”, …)
```

PERFORMANCE

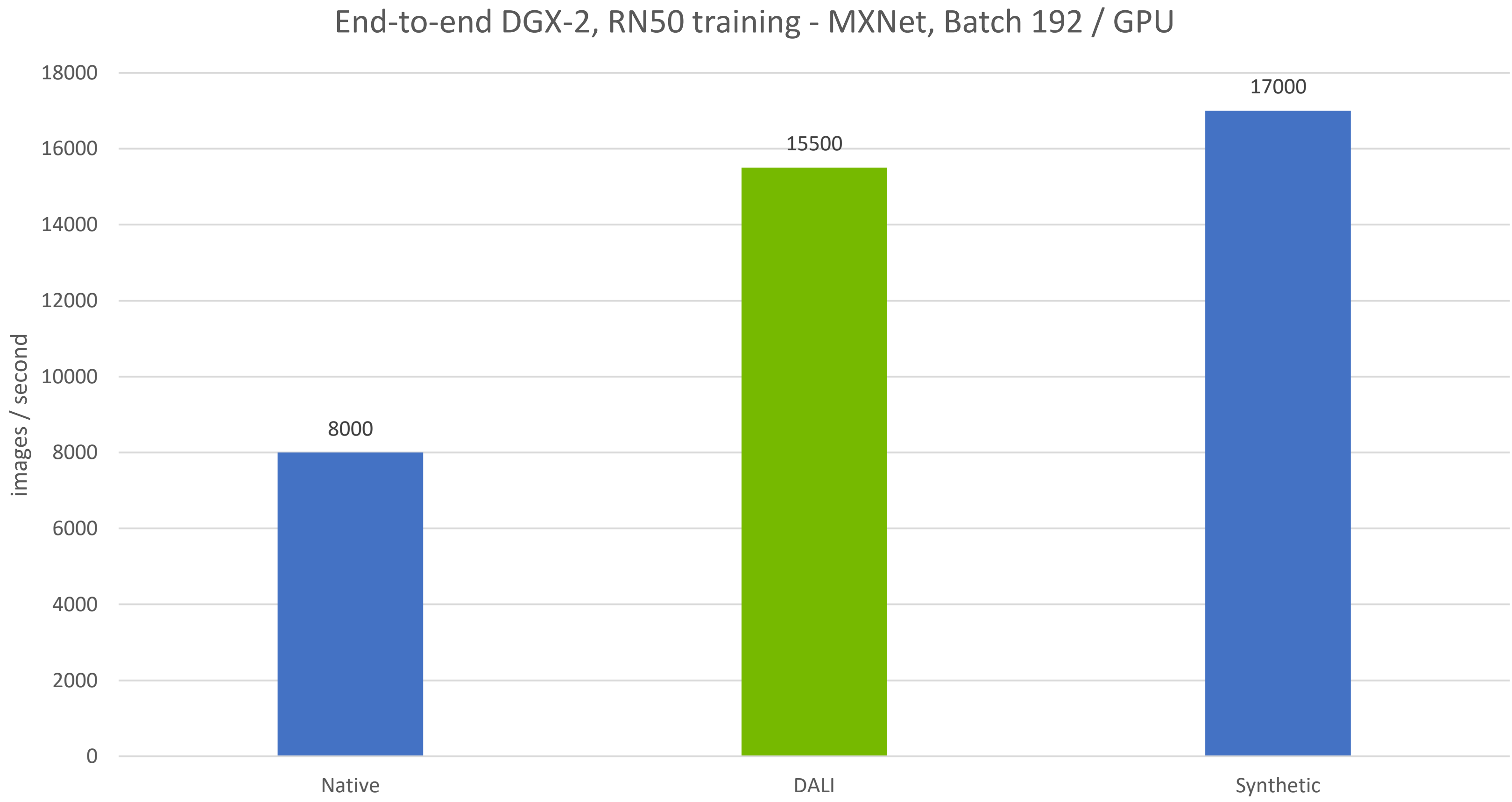
PERFORMANCE

I/O Pipeline



PERFORMANCE

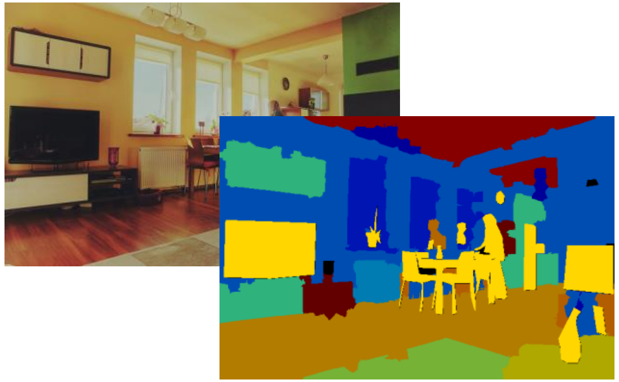
End-to-end training



NEXT STEPS

NEXT: MORE WORKLOADS

Segmentation



```
def define_graph(self):
  images, masks = self.loader(name="Reader")
  images = self.decode(images)
  masks = self.decode(masks)

  # Apply identical transformations
  resized_images, resized_masks = self.resize([images, masks], …)
  cropped_images, cropped_masks = self.crop([resized_images,
                                              resized_masks], …)
  return [cropped_images, cropped_masks]
```

NEXT: MORE FORMATS

What would be useful to you?

PNG

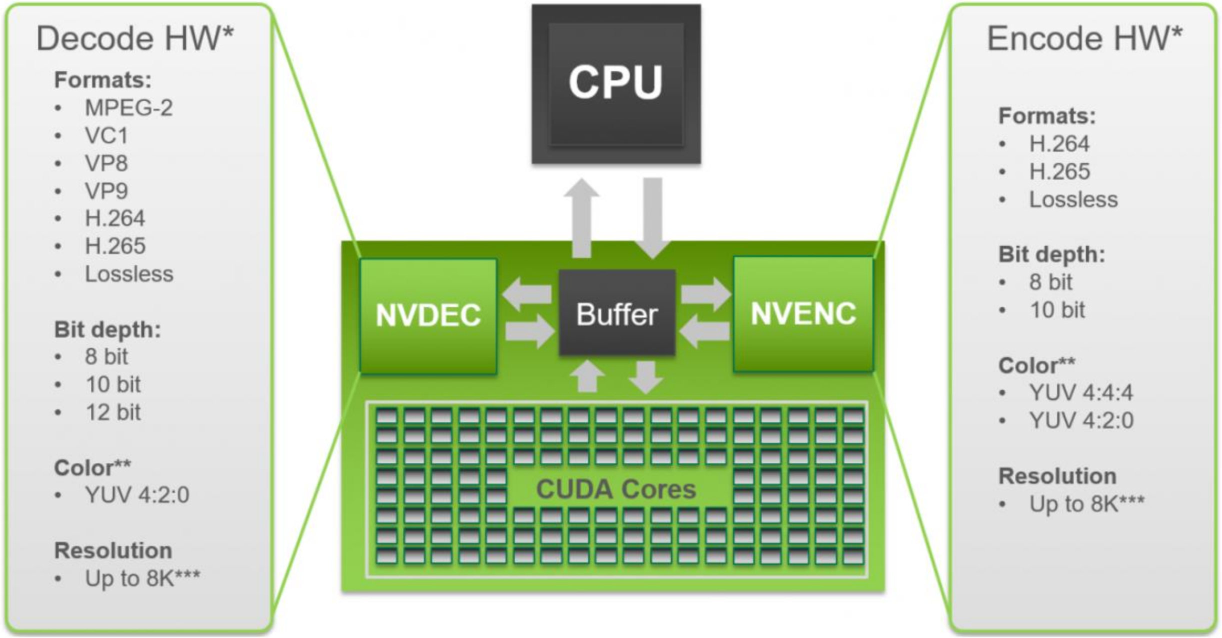
Video frames

NEXT++: MORE OFFLOADING

Fully GPU-based decode

HW-based via. NVDEC

Transcode to video



SOON: EARLY ACCESS

Looking for:

General feedback

New workloads

New transformations

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NVIDIA