MXNet: Flexible and Efficient Library for Deep Learning

from Distributed GPU Clusters to Embedded Systems

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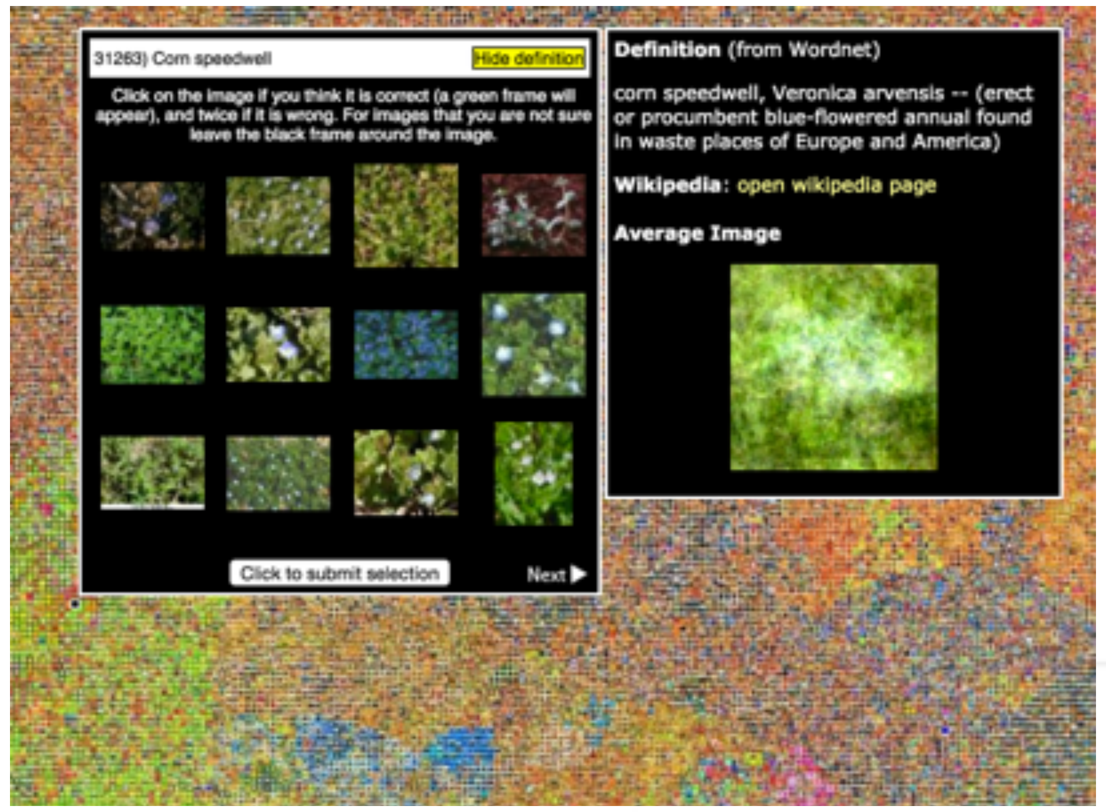
Deep Learning

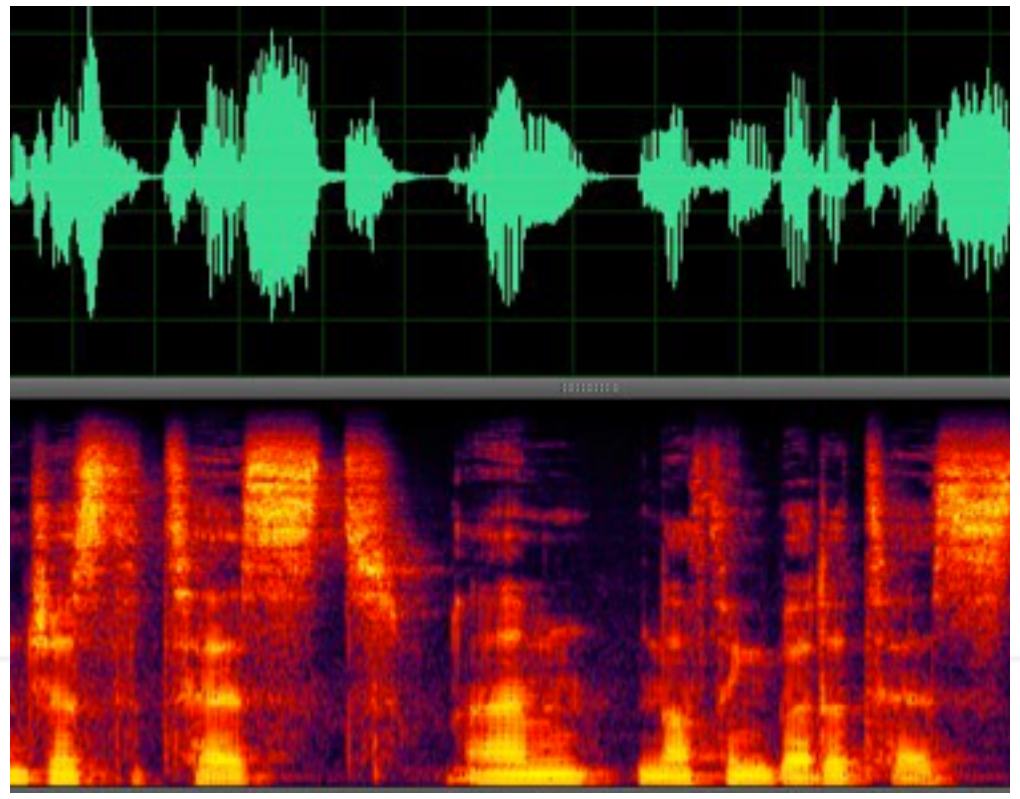
Learns multiple levels of representations of data

Significantly improve many applications on multiple domains

image understanding

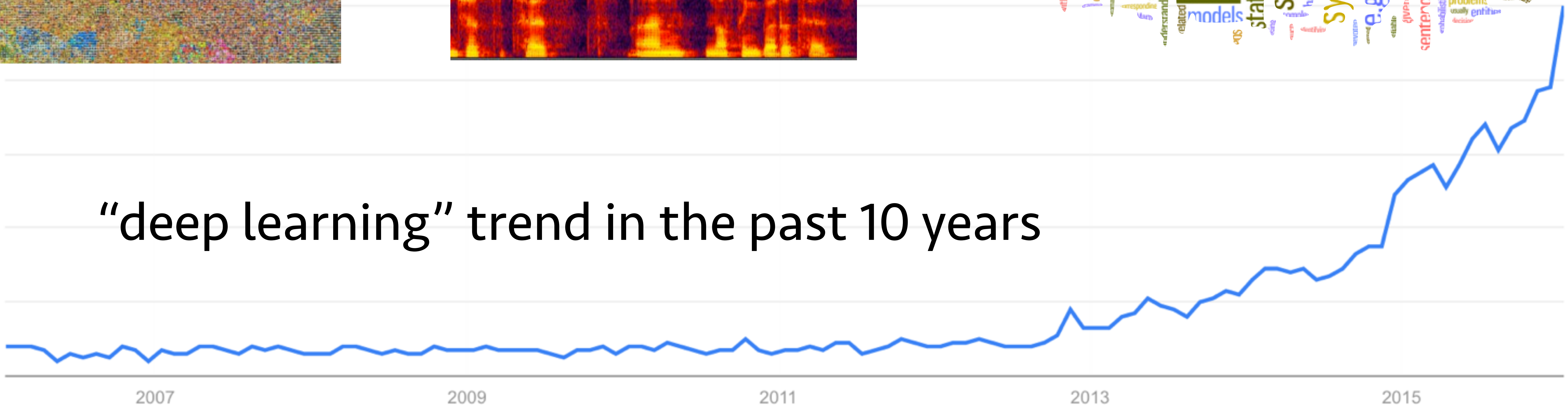


speech recognition



natural language processing

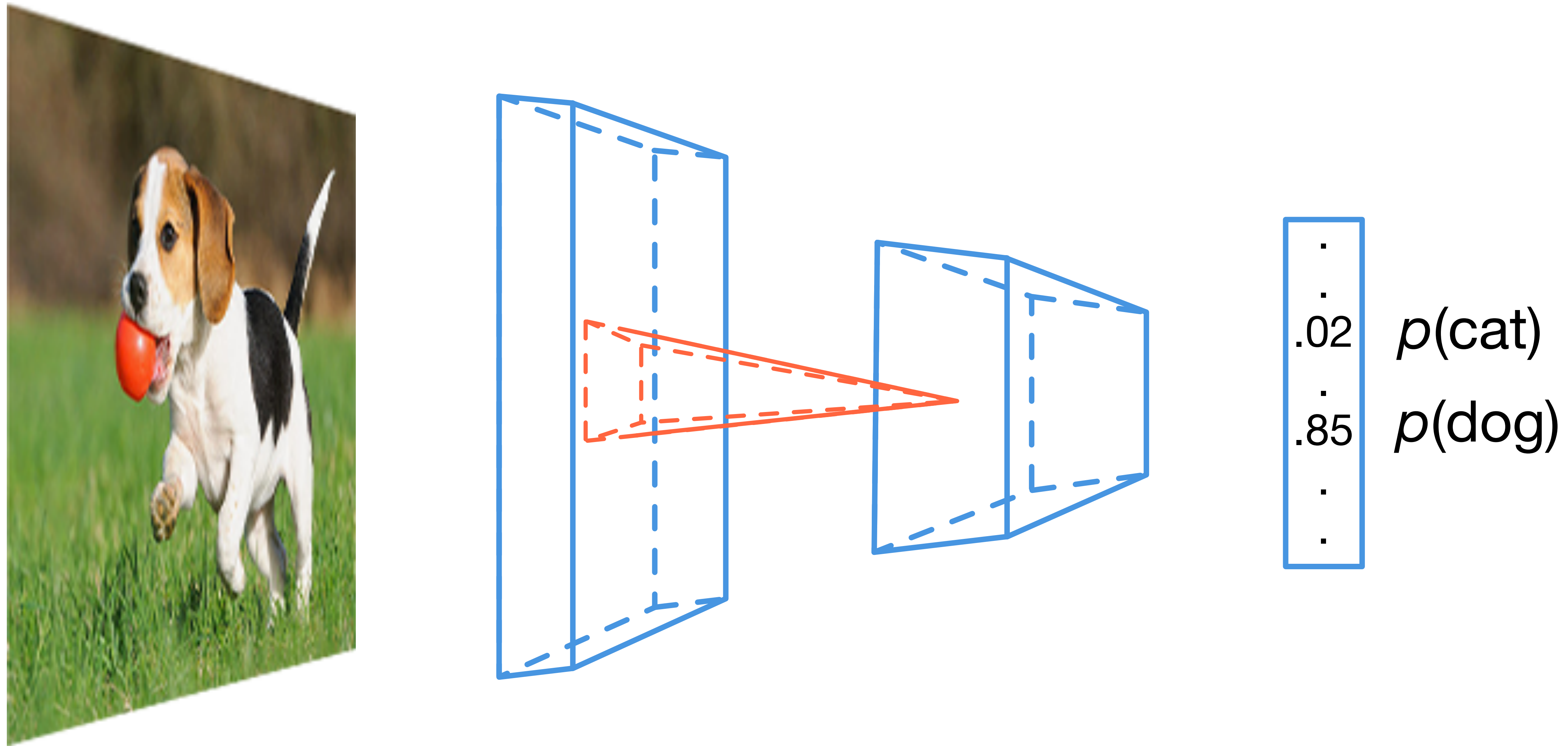
…



“deep learning” trend in the past 10 years

Image classification

multilevel feature extractions from raw pixels
to semantic meanings

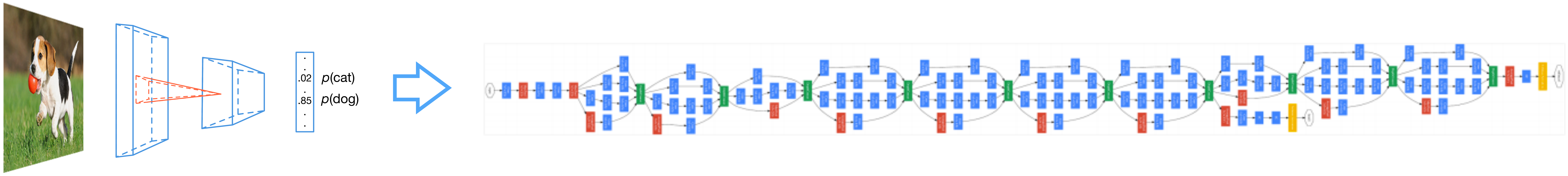


Layer 1 Layer 2 Output

explore spatial information with convolution layers

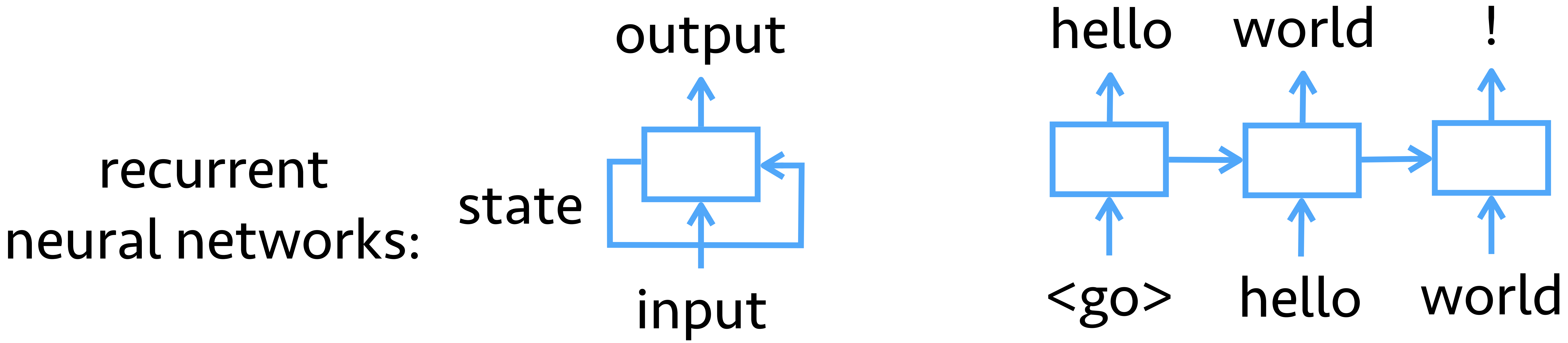
Image Classification

State-of-the-art networks have tens to hundreds layers



- Hard to define the network
  - the definition of the inception network has >1k lines of codes in Caffe
- A single image requires billions floating-point operations
  -  Intel i7 ~500 GFLOPS
  -  Nvidia Titan X: ~5 TFLOPS
- Memory consumption is linear with number of layers

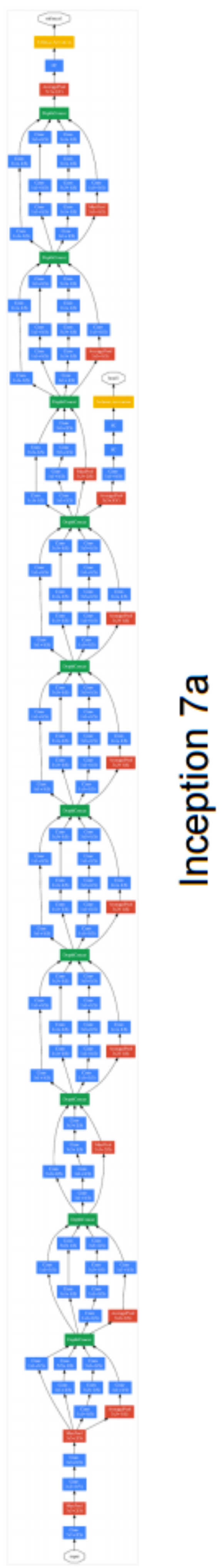
Language Modeling



- Variable length of input and output sequences
- State-of-the-art networks have many layers
  - Billions of floating-point operations per sentence
  - Memory consumption is linear with both sequence length and number of layers

MXNet Highlights

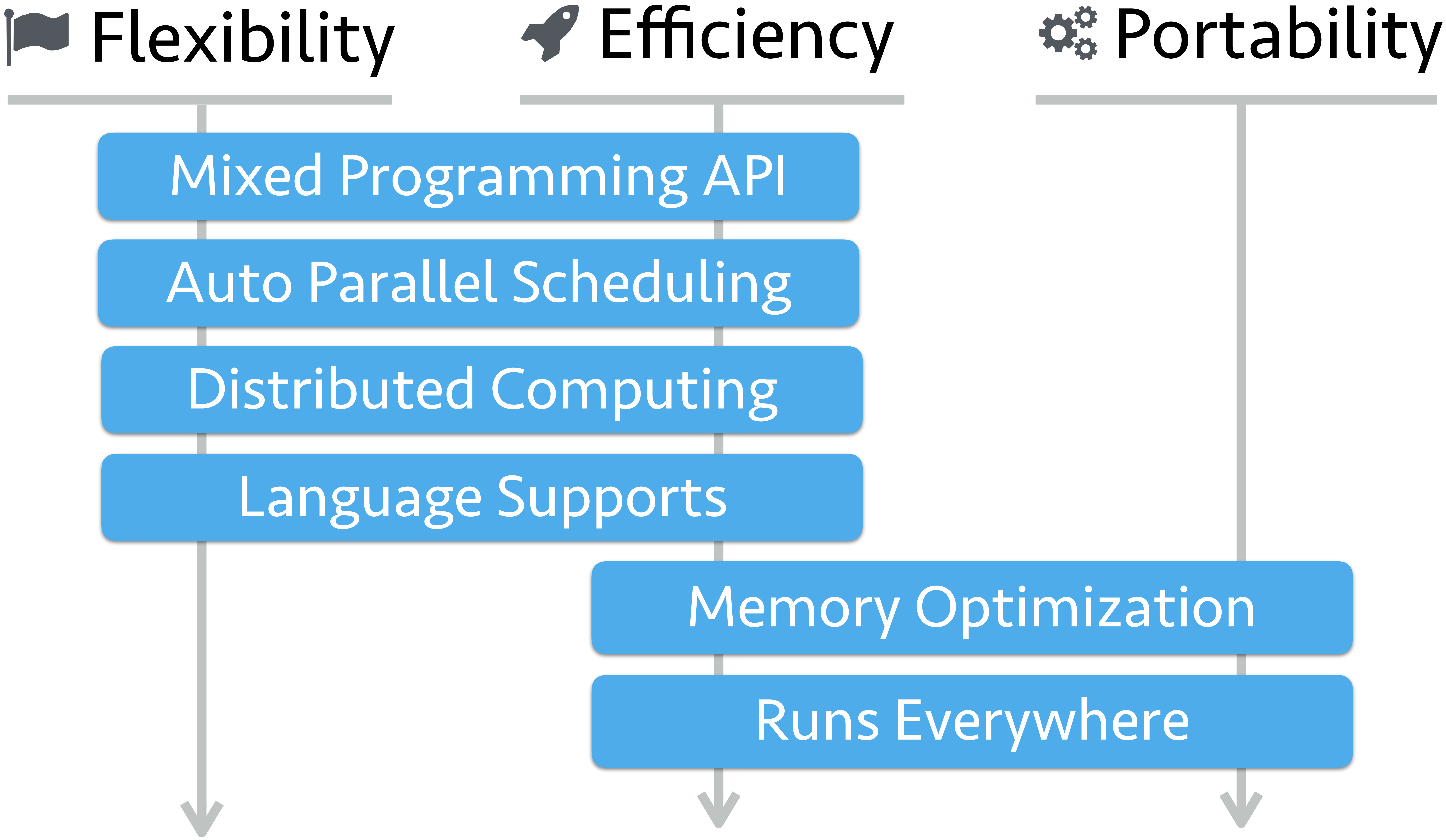
Flexibility



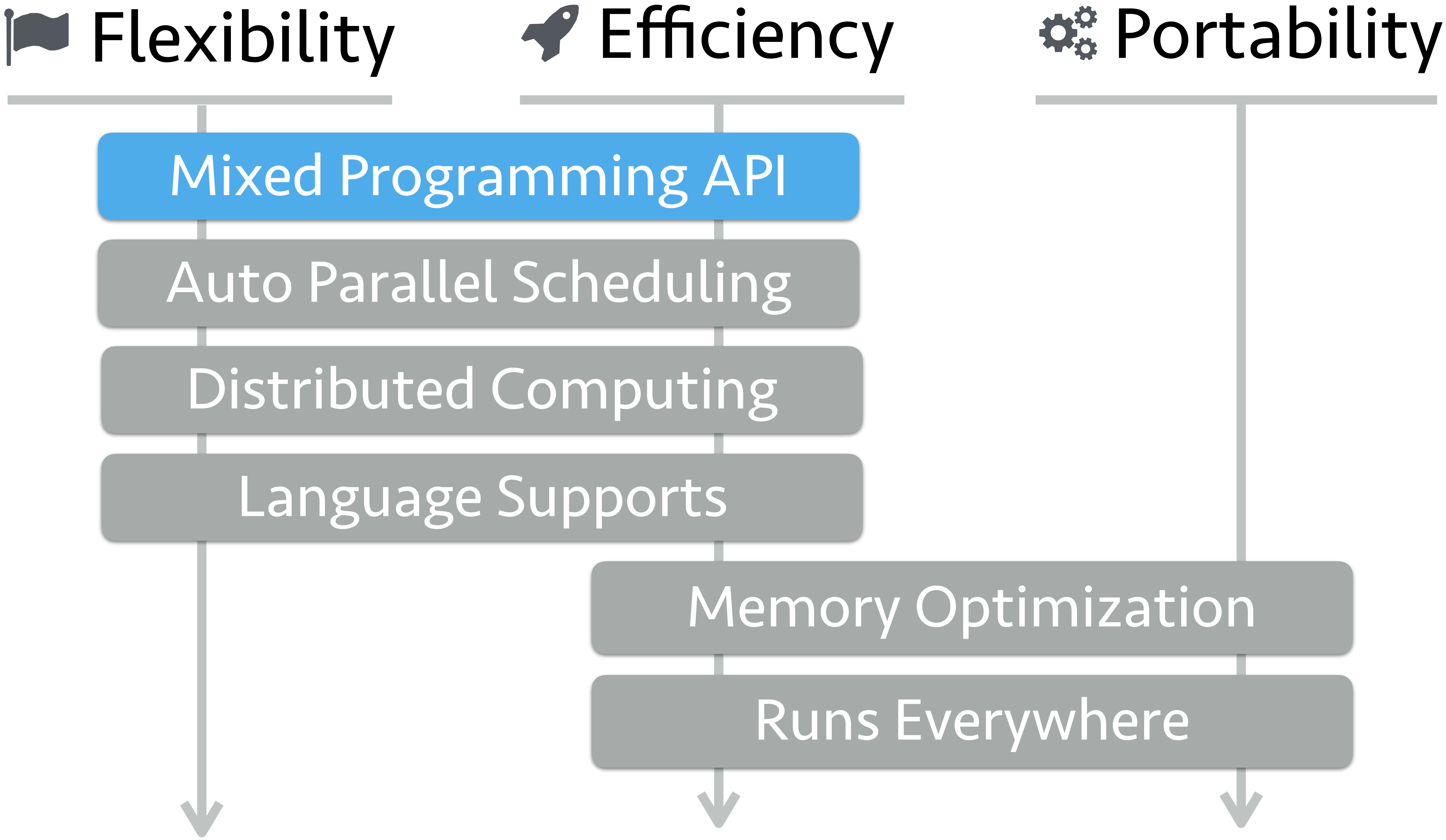
Efficiency

Portability

MXNet Highlights

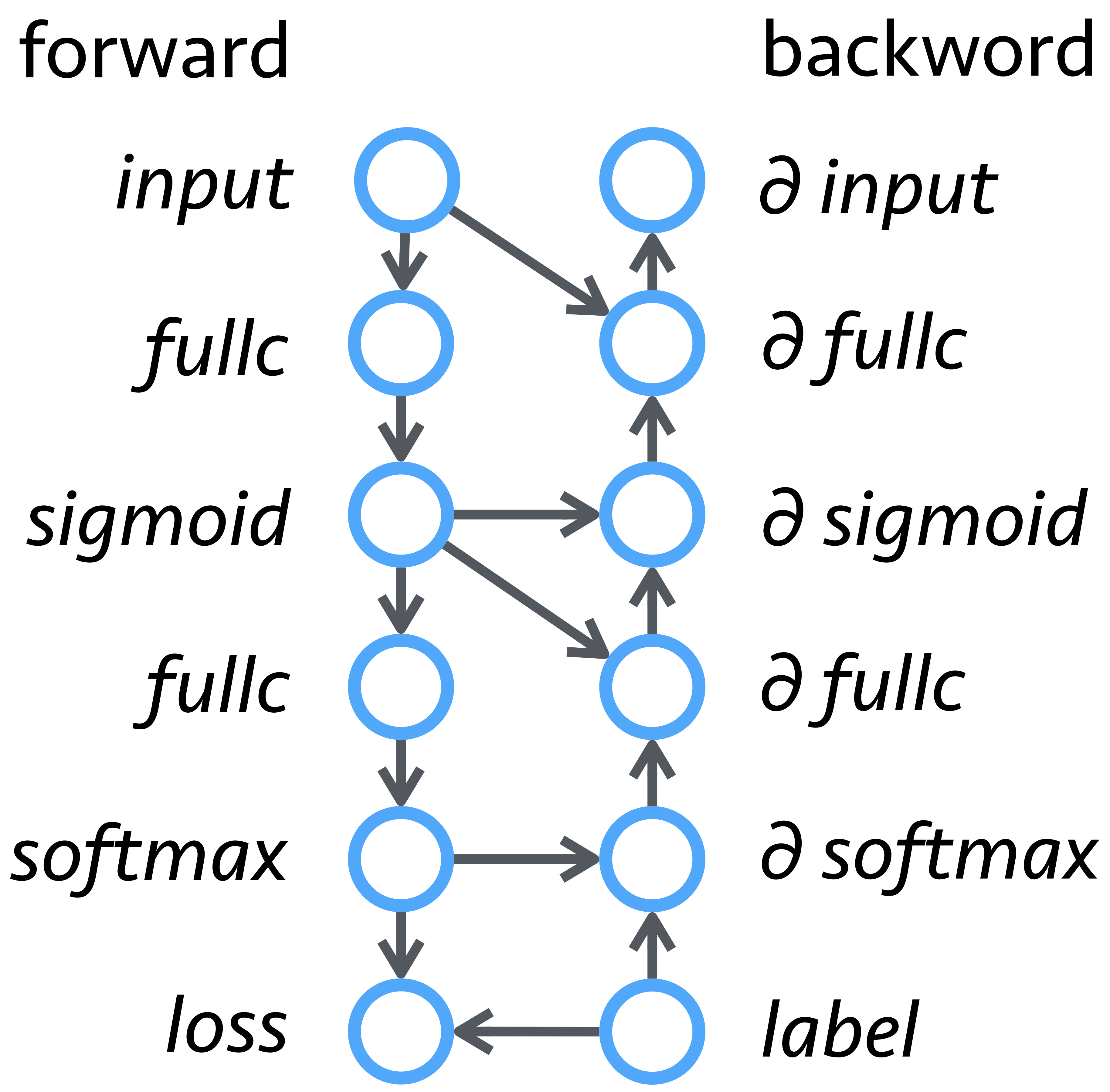


MXNet Highlights



Deep Learning Workflow

Computational Graph
of the Deep Architecture



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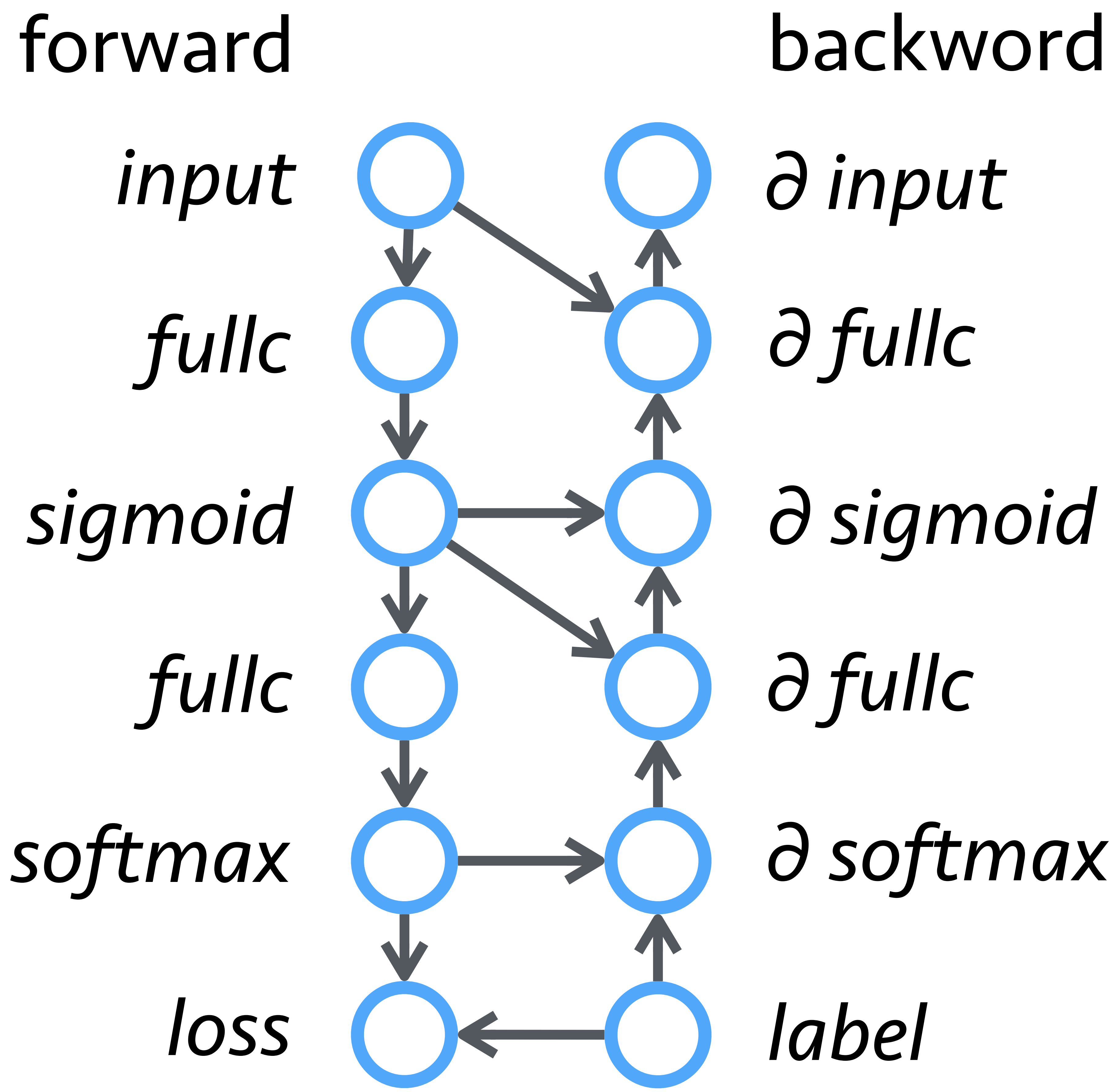
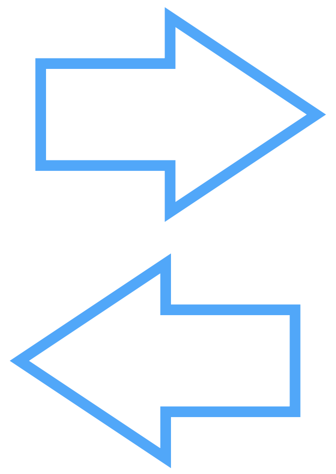


Updates and Interactions
with the graph

- Parameter update
- Beam search
- Feature extraction ...



$w = w - \eta\, \partial f(w)$

- Involves high dimensional array(tensor) operations in both direction
- How to program a typical DL application?

Imperative Programs

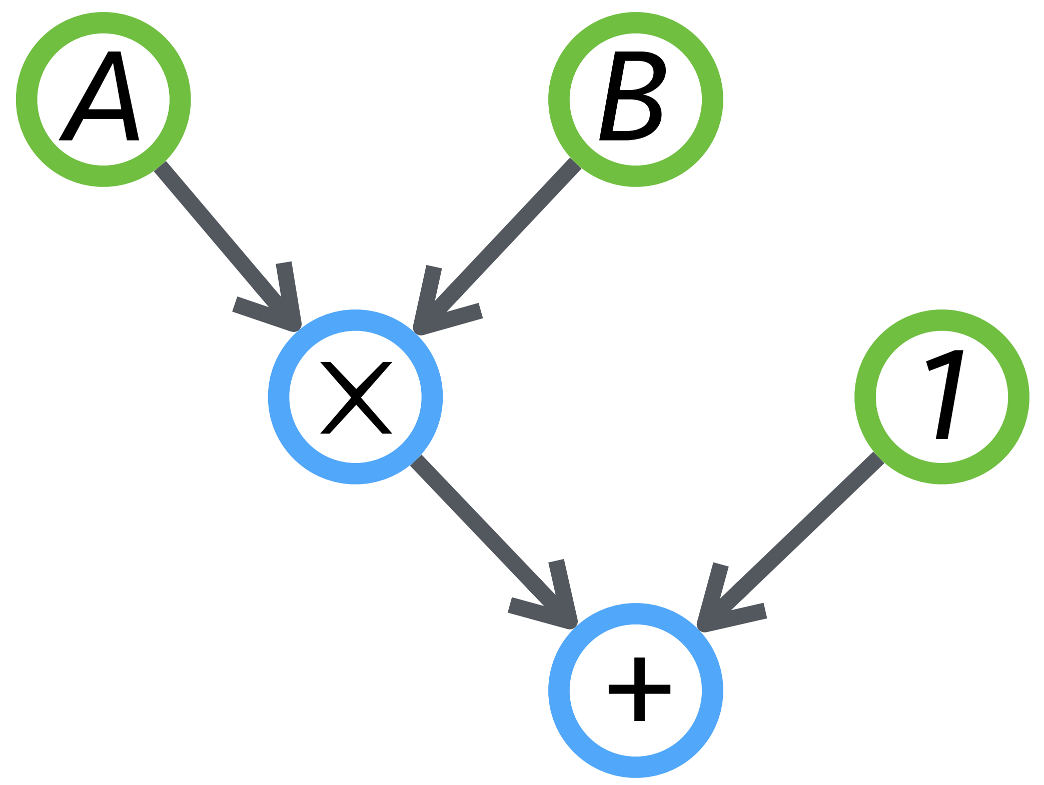
- Execute operations step by step.
- $c = b \times a$ invokes a kernel operation
- Numpy programs are imperative

```python
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
d = c + 1
```

Declarative Programs

- Declares the computation
- Compiles into a function
- $C = B \times A$ only specifies the requirement
- SQL is declarative

```
A = Variable('A')
B = Variable('B')
C = B * A
D = C + 1
f = compile(D)
d = f(A=np.ones(10), B=np.ones(10)*2)
```



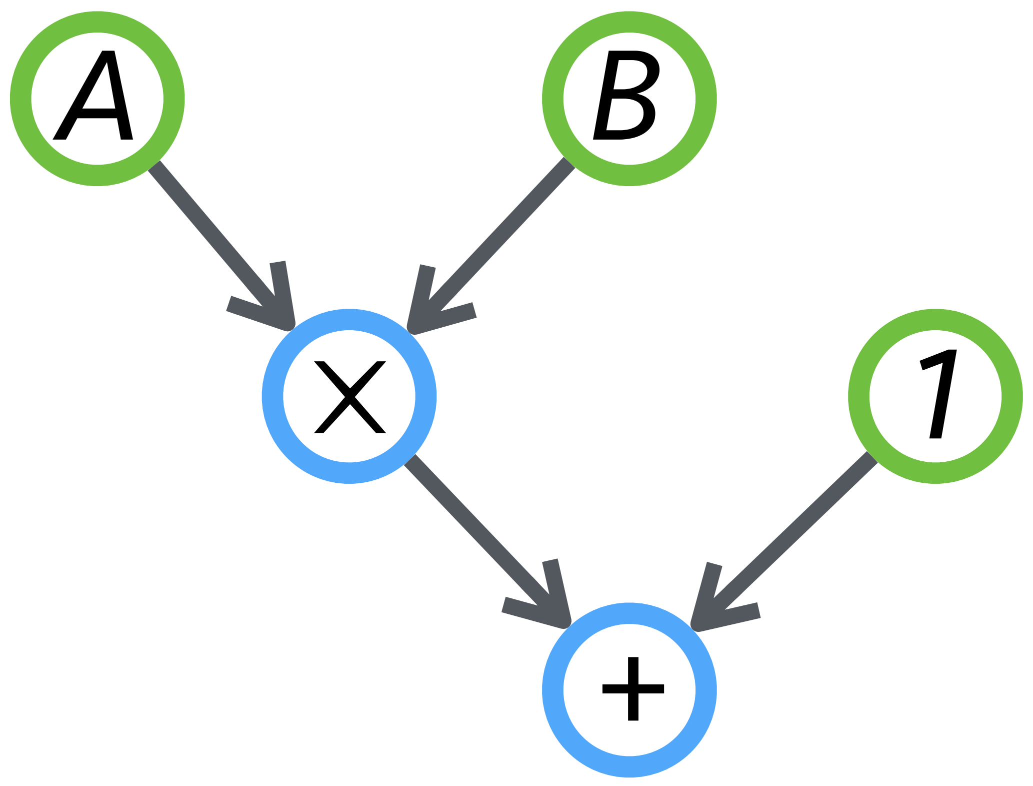
Imperative vs. Declarative Programs

- Imperative programs are straightforward and flexible.
- Take advantage of language native features (loop, condition)

```
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
print(c)
d = c + 1
```

Easy to tweak with python codes

```
A = Variable('A')
B = Variable('B')
C = B * A
D = C + 1
f = compile(D)
d = f(A=np.ones(10), B=np.ones(10)*2)
```



Imperative vs. Declarative Programs

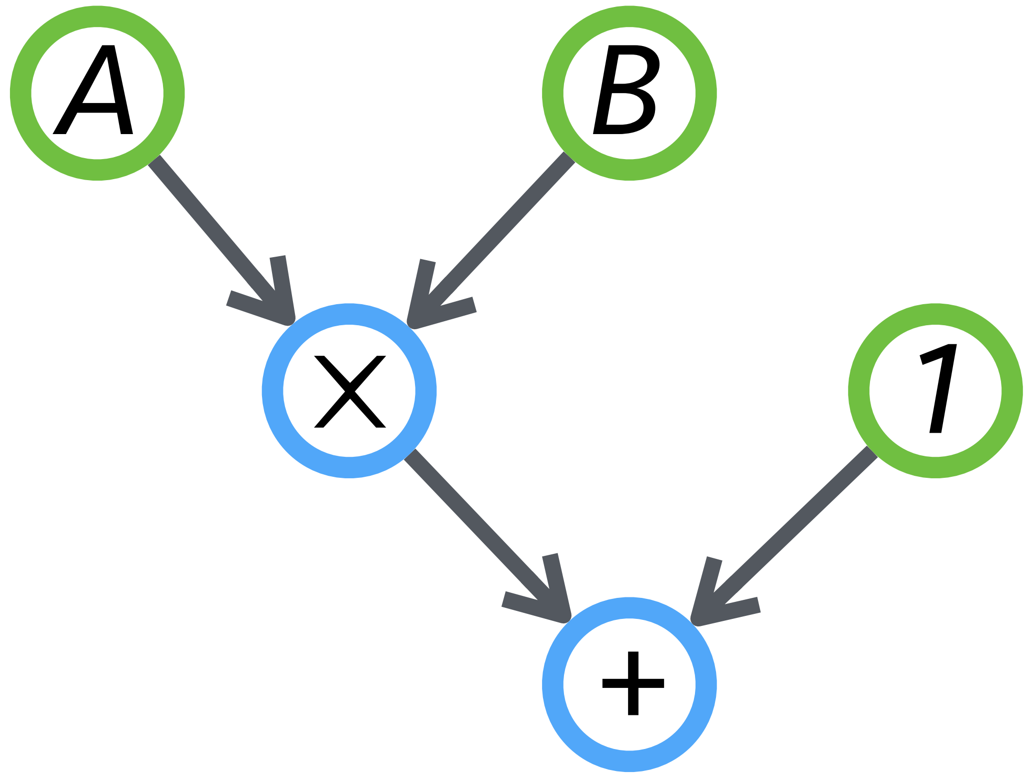
- Declarative programs see the entire graph
- More chances for optimization
- Easy to save and load the computation structure

Which program uses less memory to obtain *d*?

```
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
d = c + 1
```

c **cannot** share memory with *d*, because it could be used in future

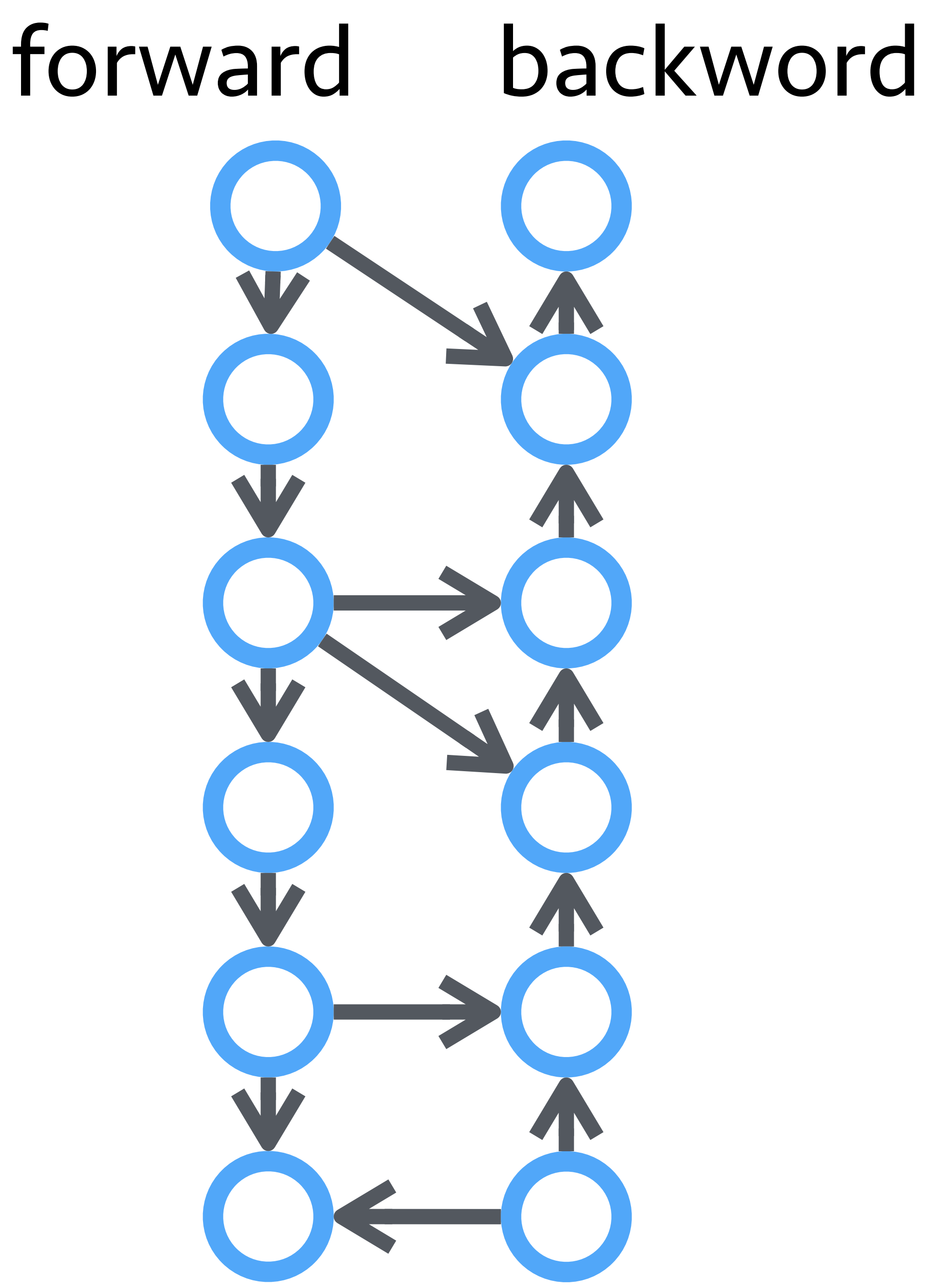
```
A = Variable('A')
B = Variable('B')
C = B * A
D = C + 1
f = compile(D)
d = f(A=np.ones(10), B=np.ones(10)*2)
```

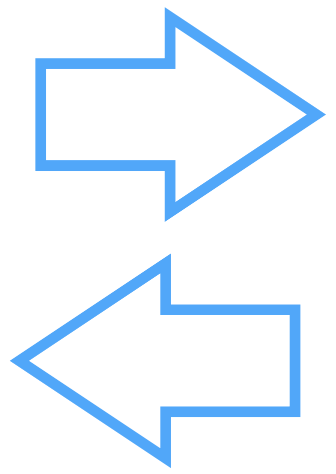


C **can** share memory with *D*, because C cannot be seen by user

Imperative vs. Declarative for Deep Learning

Computational Graph
of the Deep Architecture





Needs heavy optimization,
fits **declarative** programs

Updates and Interactions
with the graph

- Parameter update
- Beam search
- Feature extraction ...

$$w = w - \eta\, \partial f(w)$$

Needs mutation and more
language native features, good for
imperative programs

MXNet: Mix the Flavors Together

Imperative
NDArray API

```
>>> import mxnet as mx
>>> a = mx.nd.zeros((100, 50))
>>> a.shape
(100L, 50L)
>>> b = mx.nd.ones((100, 50))
>>> c = a + b
>>> b += c
```

Declarative
Symbolic Executor

```
>>> import mxnet as mx
>>> net = mx.symbol.Variable('data')
>>> net = mx.symbol.FullyConnected(data=net, num_hidden=128)
>>> net = mx.symbol.SoftmaxOutput(data=net)
>>> type(net)
<class ‘mxnet.symbol.Symbol’>
>>> texec = net.simple_bind(data=data_shape)
```

Mixed Style Training Loop in MXNet

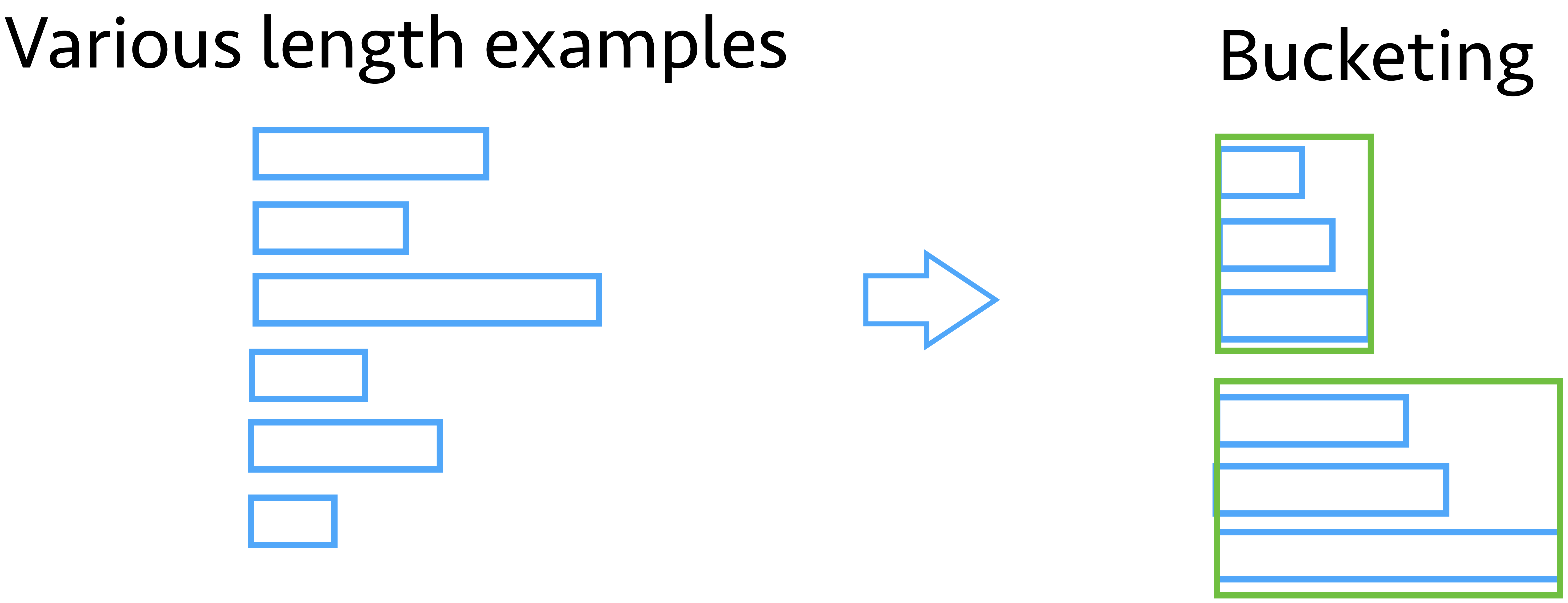
Imperative NDArray can be set as input nodes to the graph

```
executor = declarative_symbol.bind()
for i in range(3):
    train_iter.reset()
    for dbatch in train_iter:
        args["data"][:] = dbatch.data[0]
        args["softmax_label"][:] = dbatch.label[0]
        executor.forward(is_train=True)
        executor.backward()
    for key in update_keys:
        args[key] -= learning_rate * grads[key]
```

Executor is binded from declarative program that describes the network

Imperative parameter update on GPU

Mixed API for Quick Extensions



- Runtime switching between different graphs depending on input
- Useful for sequence modeling and image size reshaping

Make use of imperative code in python, **10 lines** of additional python code

3D Image Construction

Dee3D

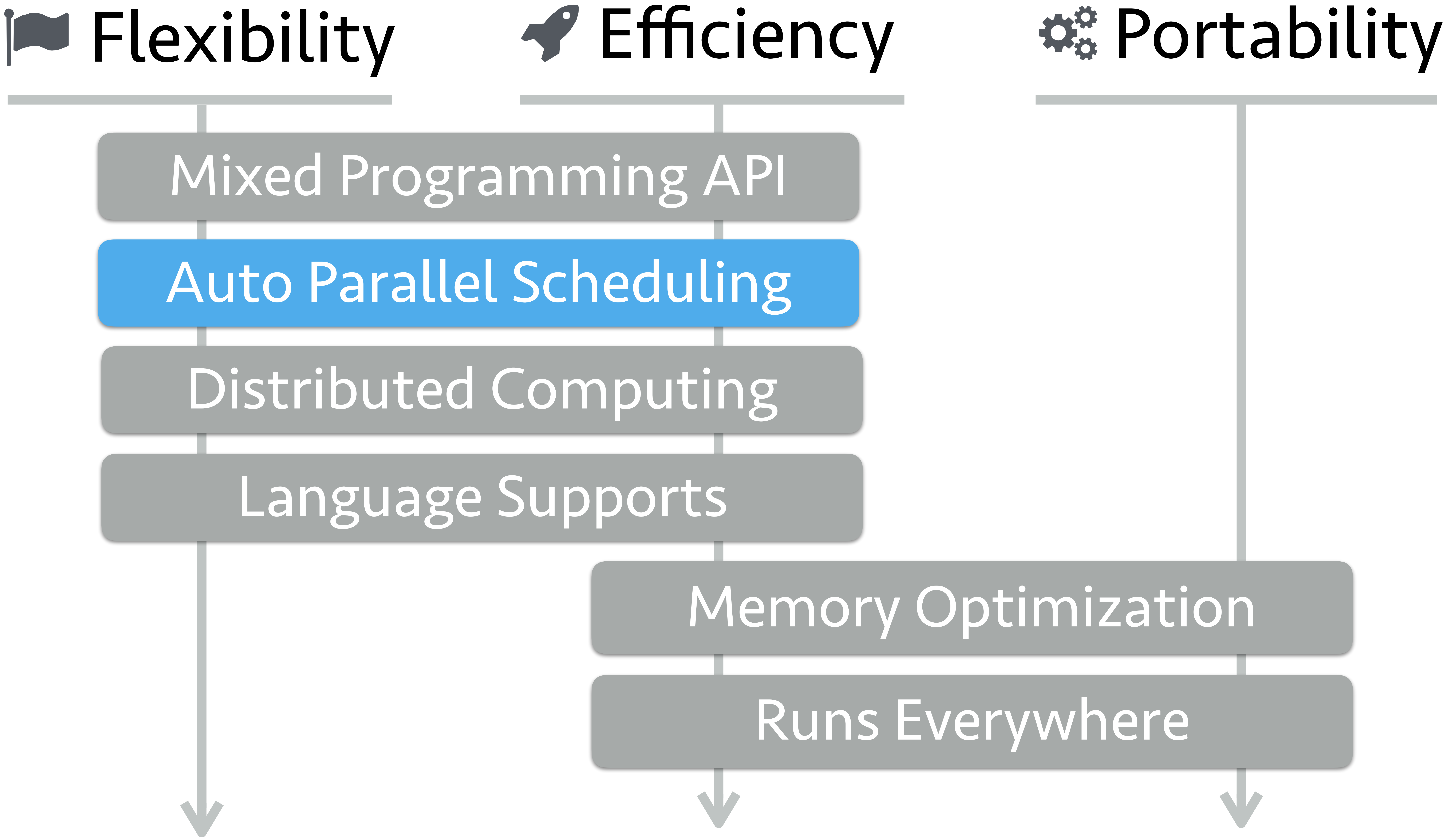
100 lines of Python codes

3D Image Construction

Dee3D

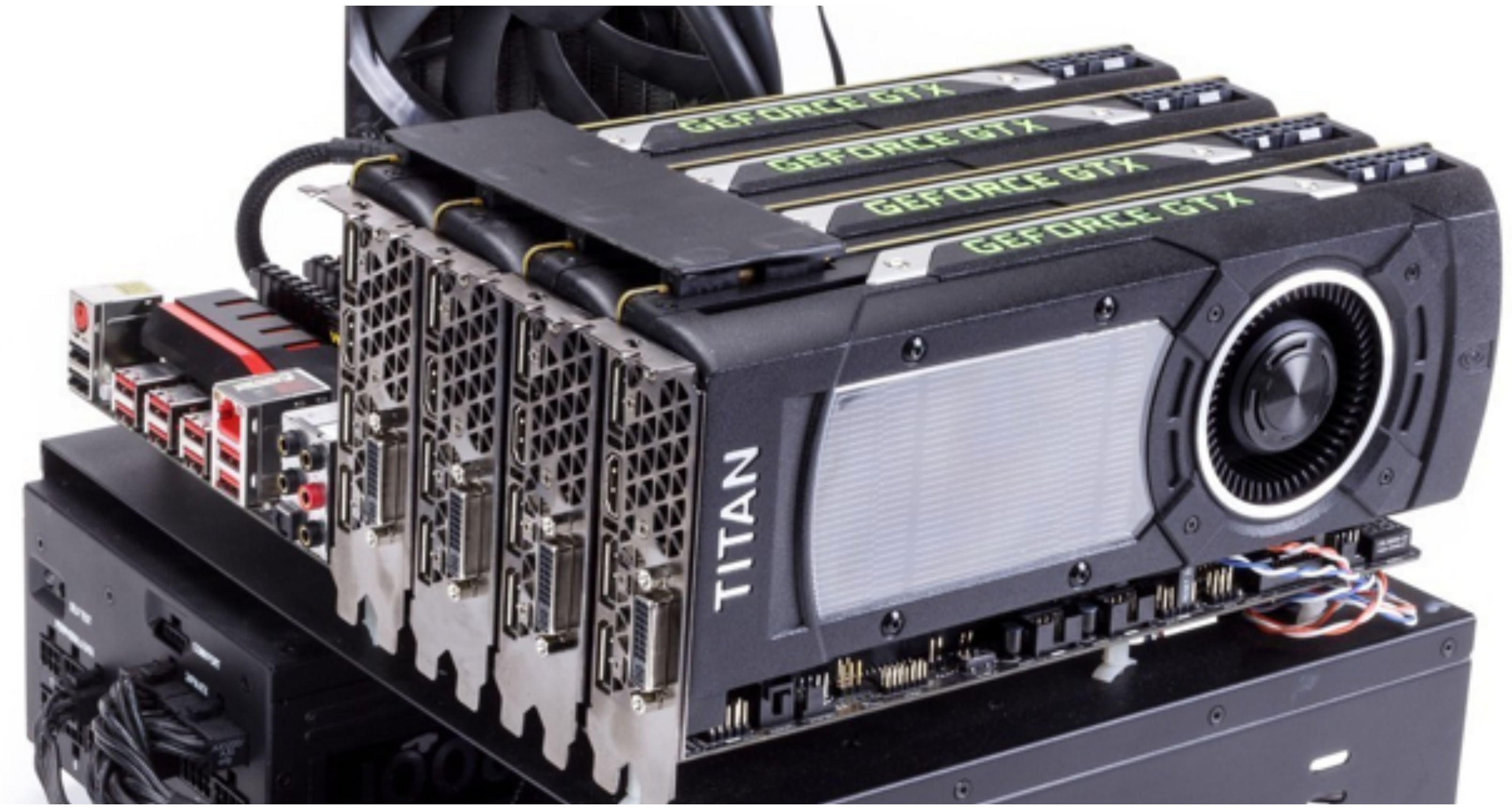
100 lines of Python codes

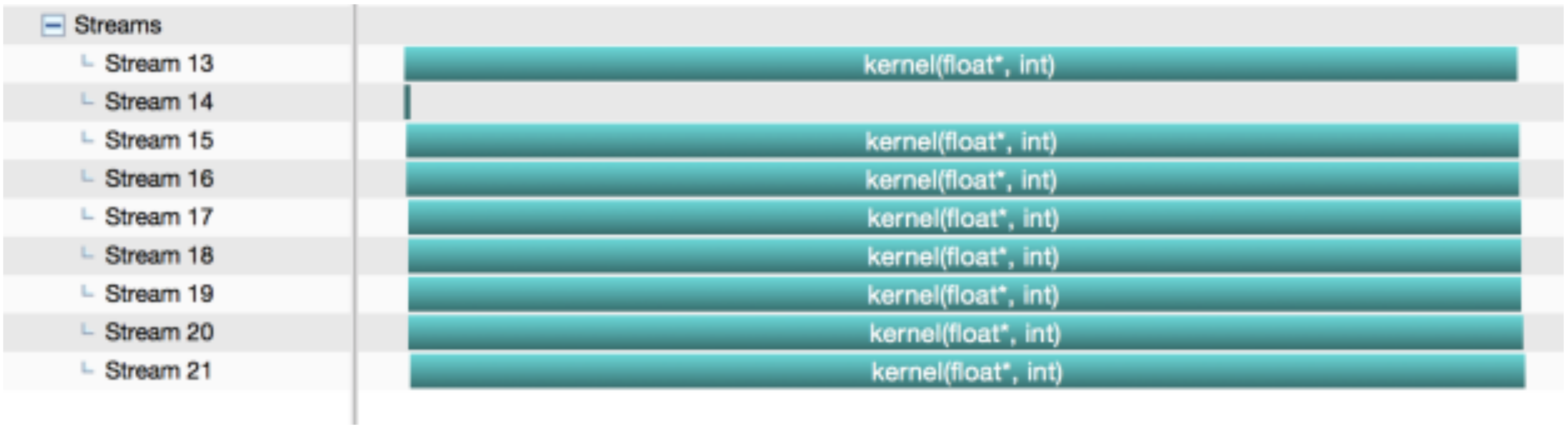
MXNet Highlights



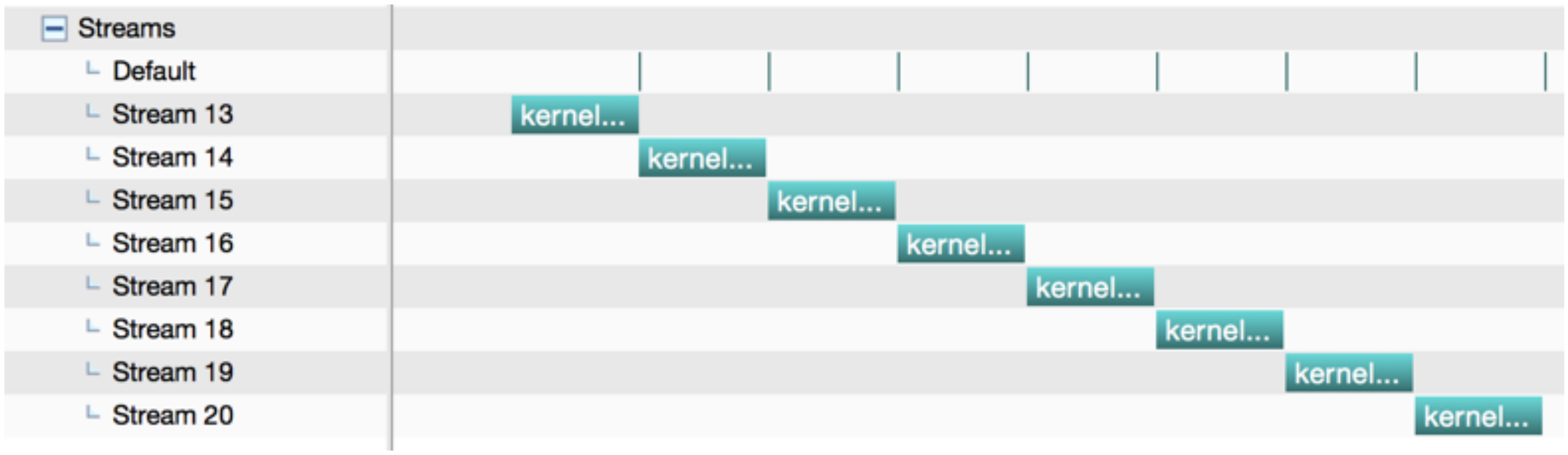
Need for Parallelization

- Parallelize workload on multiple GPUs
- Fine grained parallelization of small kernels
- Overlap of memory copy with computation





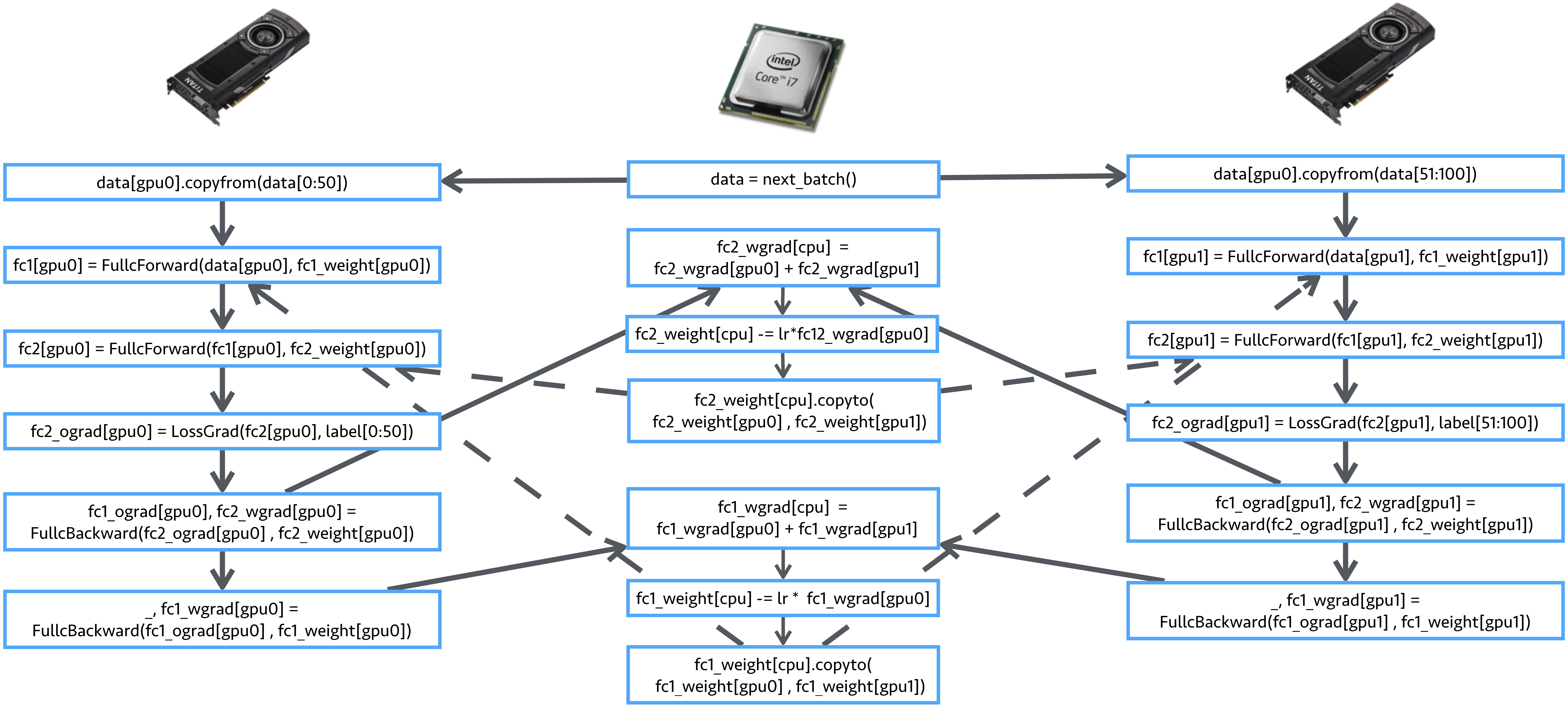
👍 Fully concurrent



👎 Serial

Writing Parallel Programs is Painful

Hard to overlap computation with communication due to dependencies

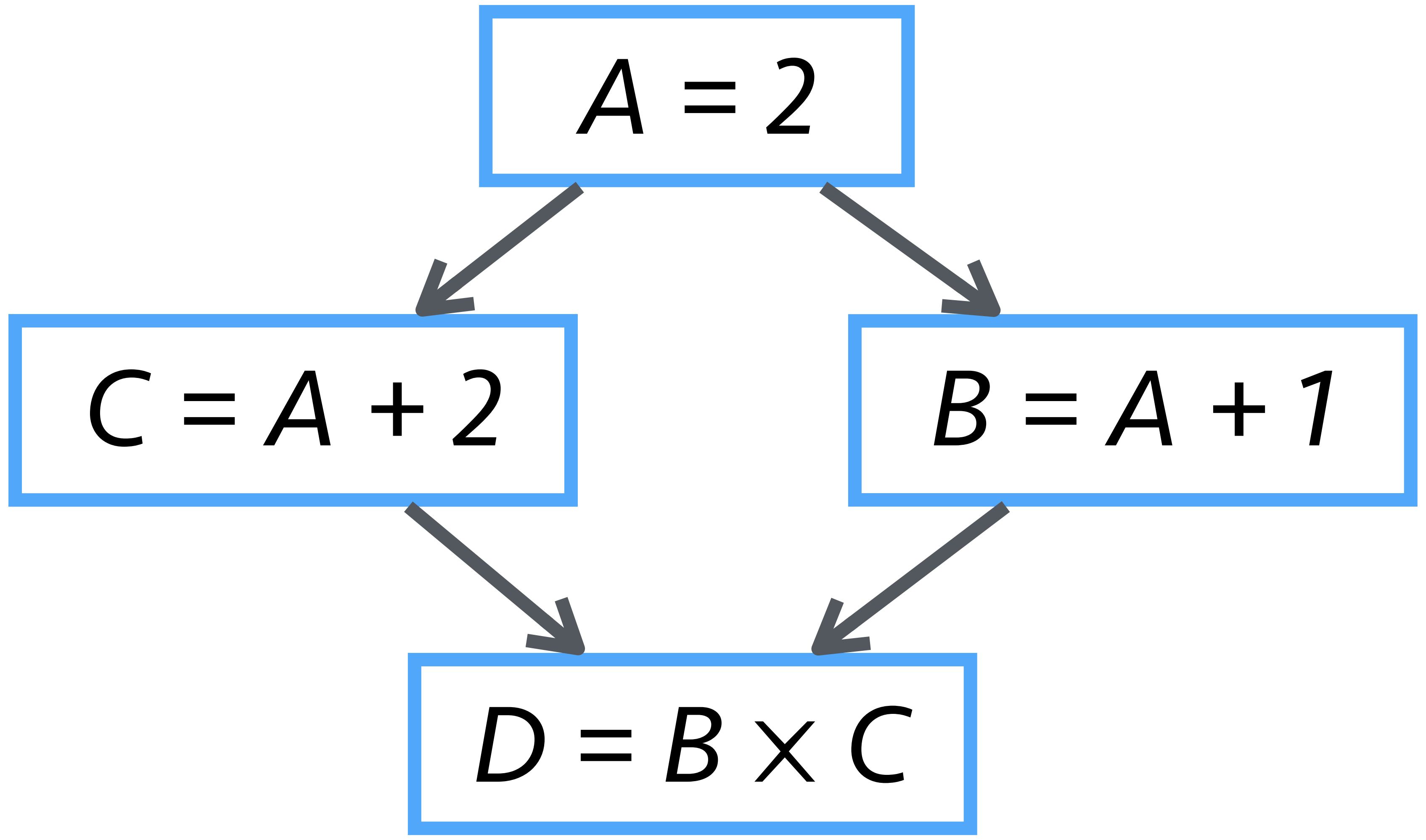


Auto Parallelization for Mixed Programs

Write **serial** programs

```
>>> import mxnet as mx
>>> A = mx.nd.ones((2,2)) *2
>>> C = A + 2
>>> B = A + 1
>>> D = B * C
```

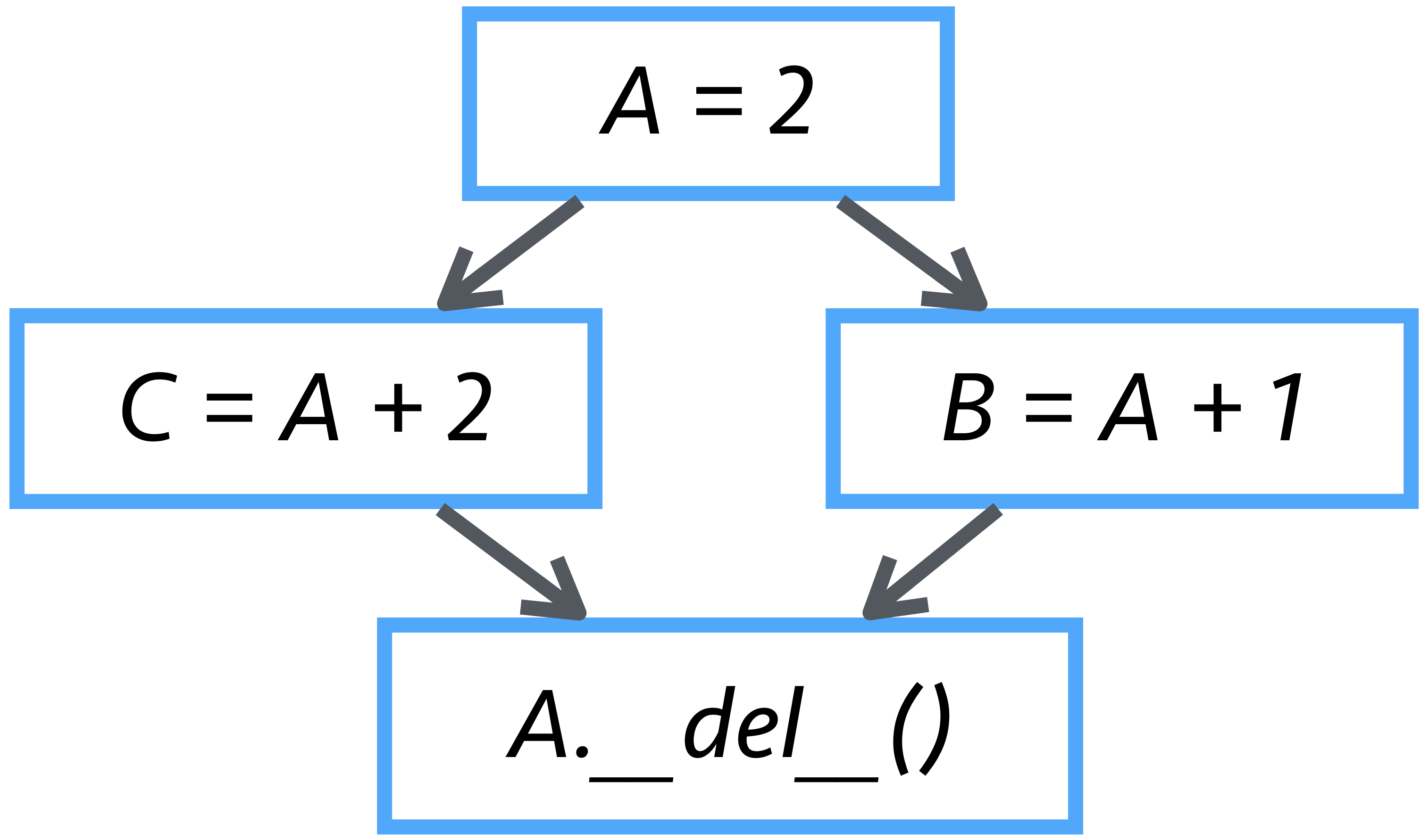
Run in **parallel**



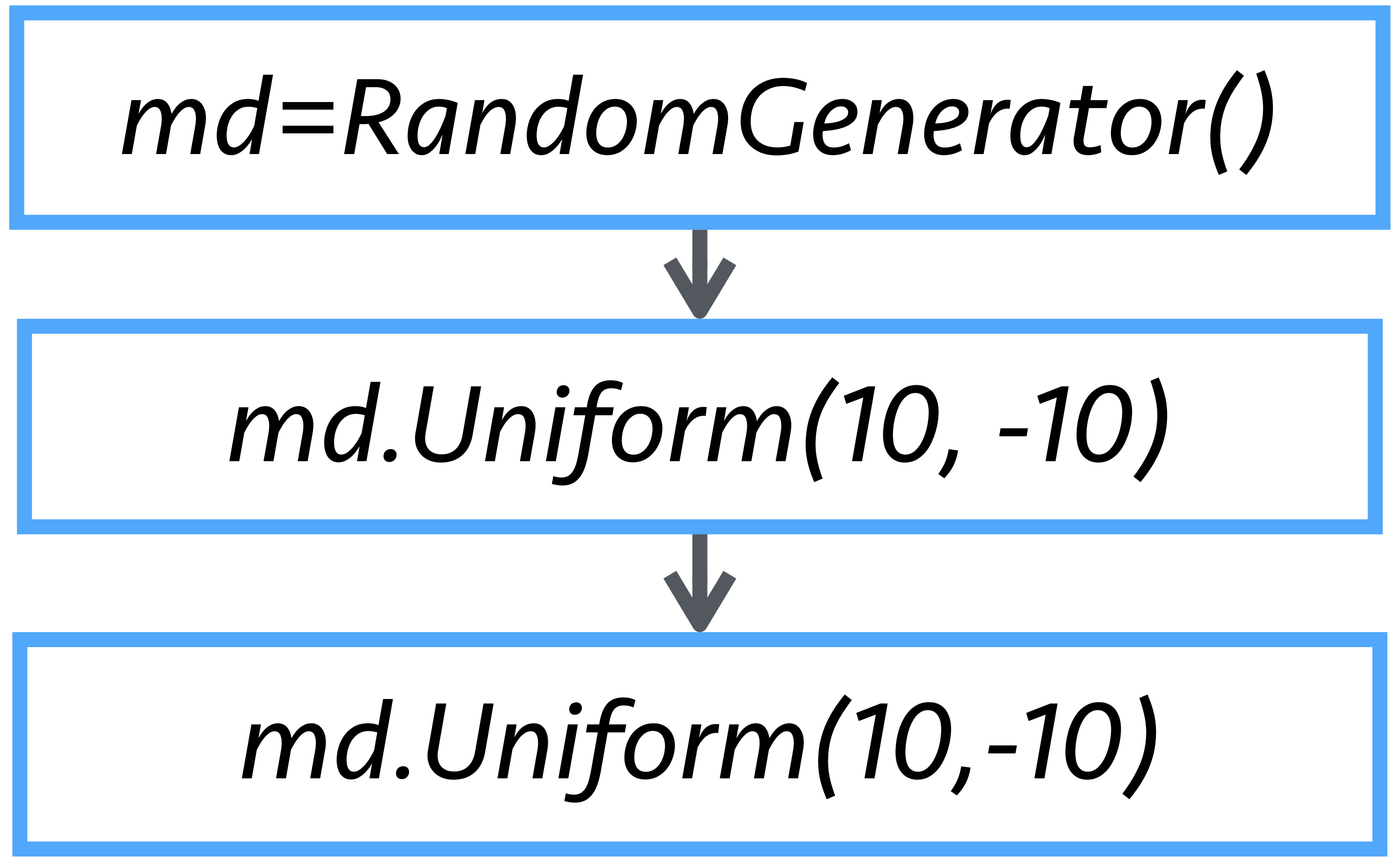
Auto Parallelization for Mixed Programs

- Schedules any resources includes array, random number generator

```
>>> import mxnet as mx
>>> A = mx.nd.ones((2,2)) *2
>>> C = A + 2
>>> B = A + 1
>>> del A
```




```
>>> import mxnet as mx
>>> A = mx.nd.uniform(shape, 10, -10)
>>> B = mx.nd.uniform(shape, 10, -10)
```



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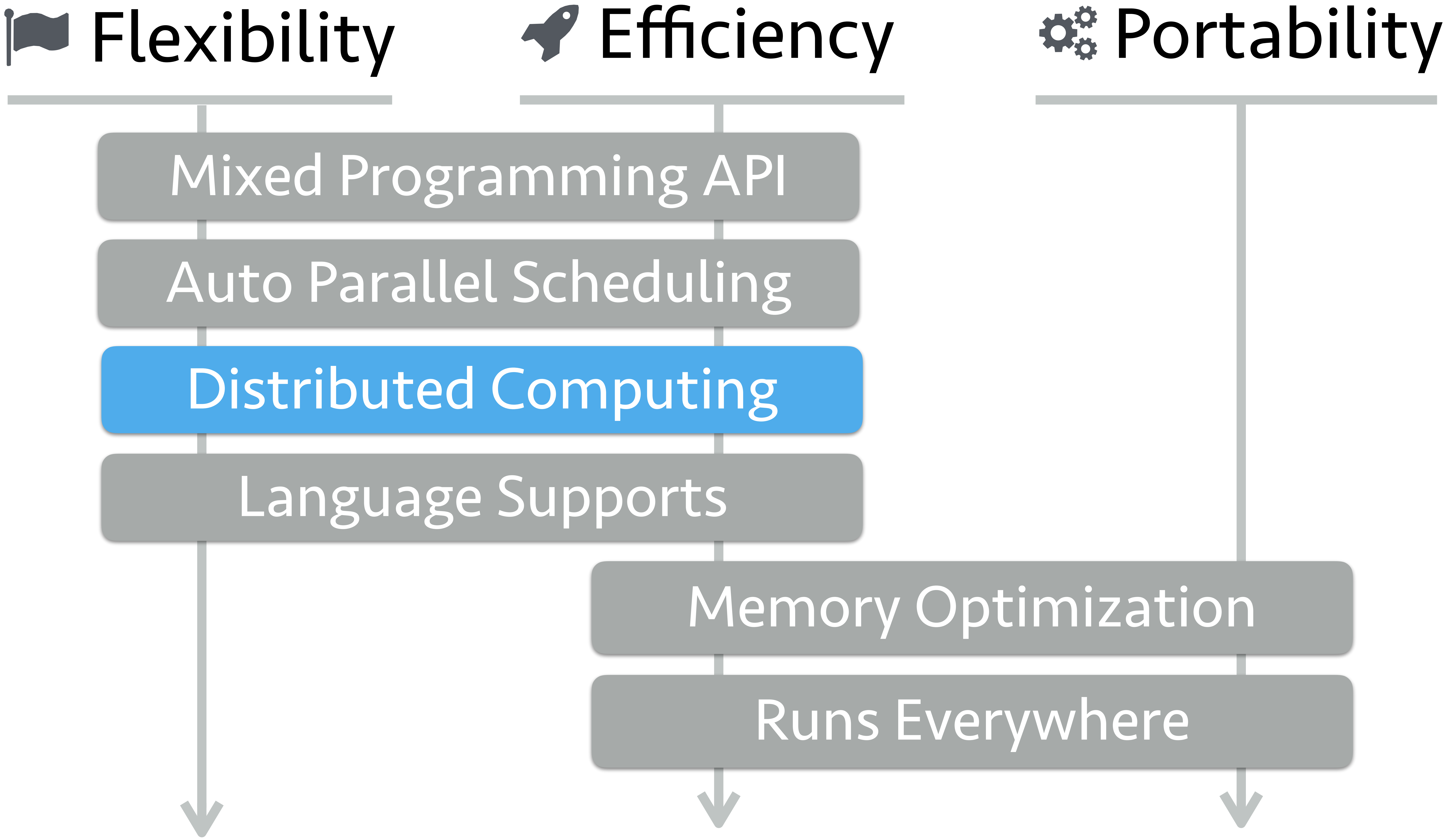
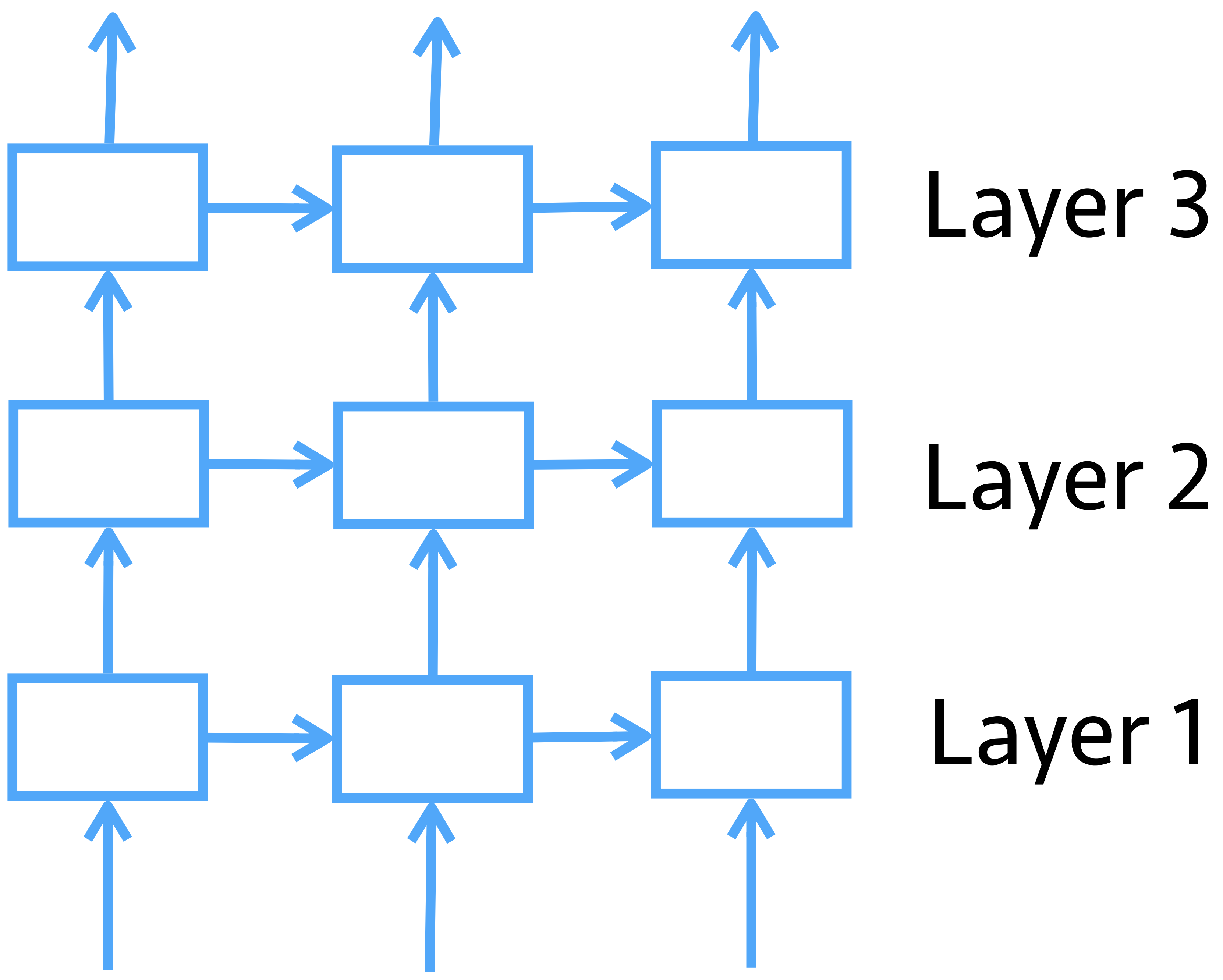


Model Parallelism



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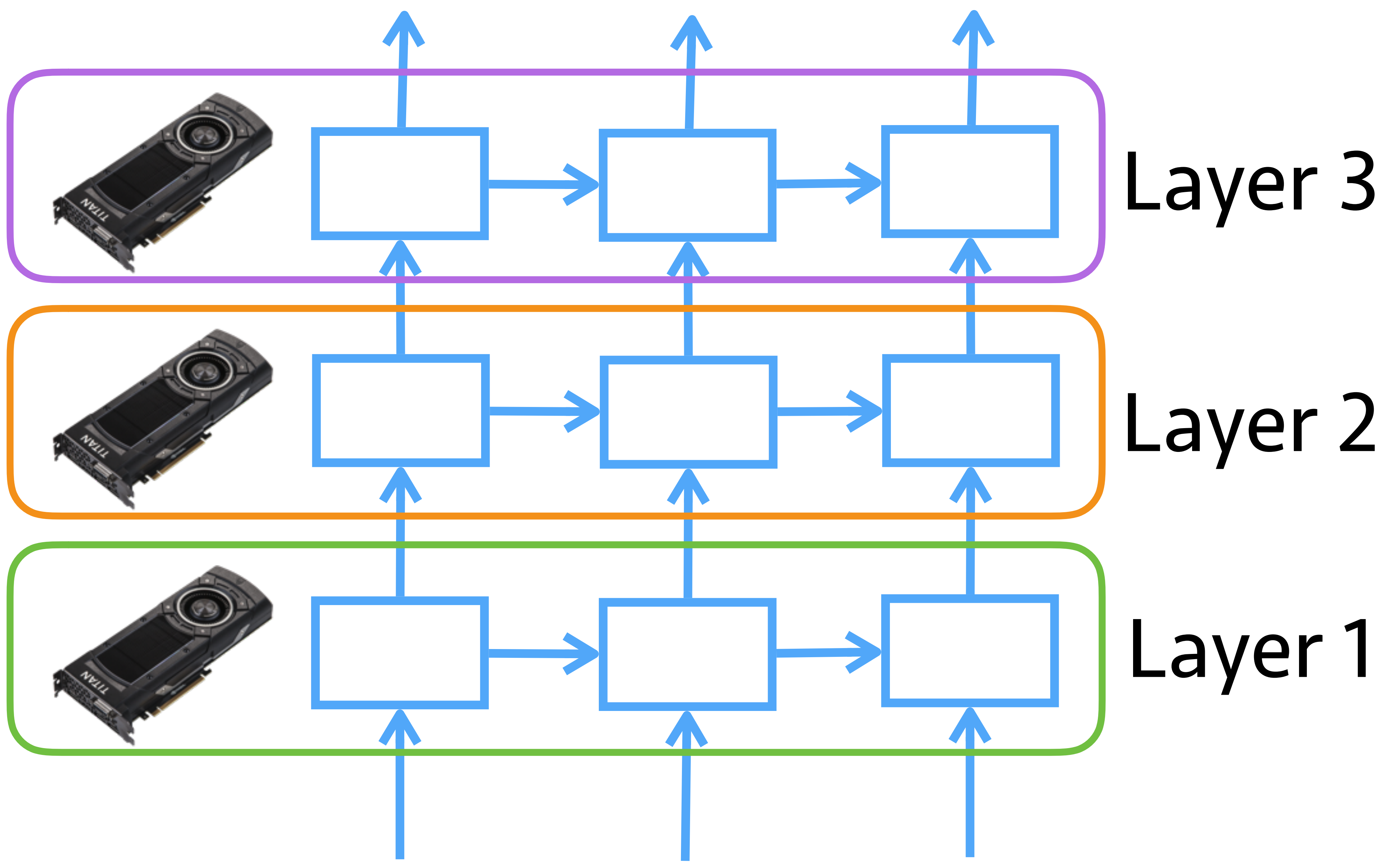

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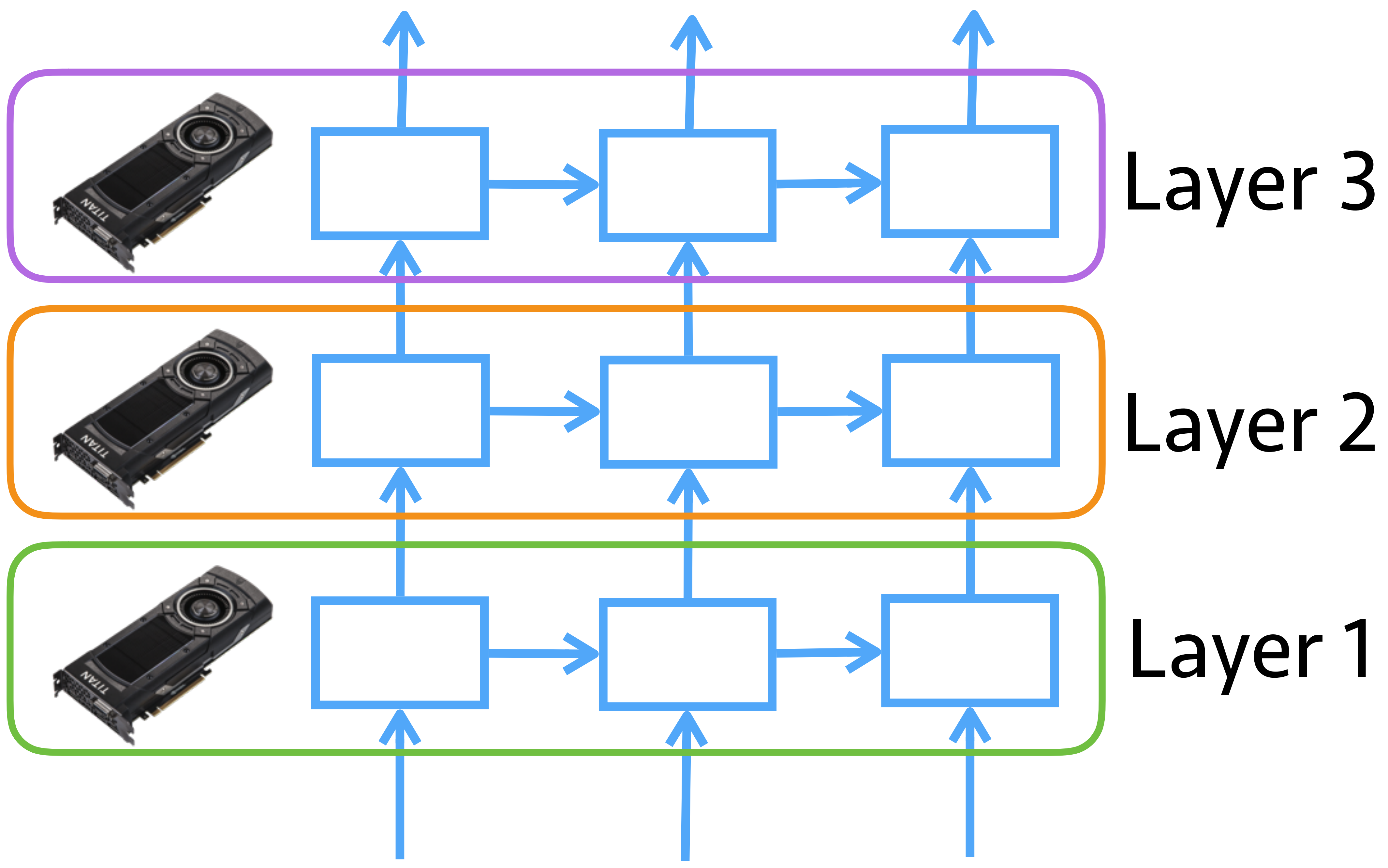
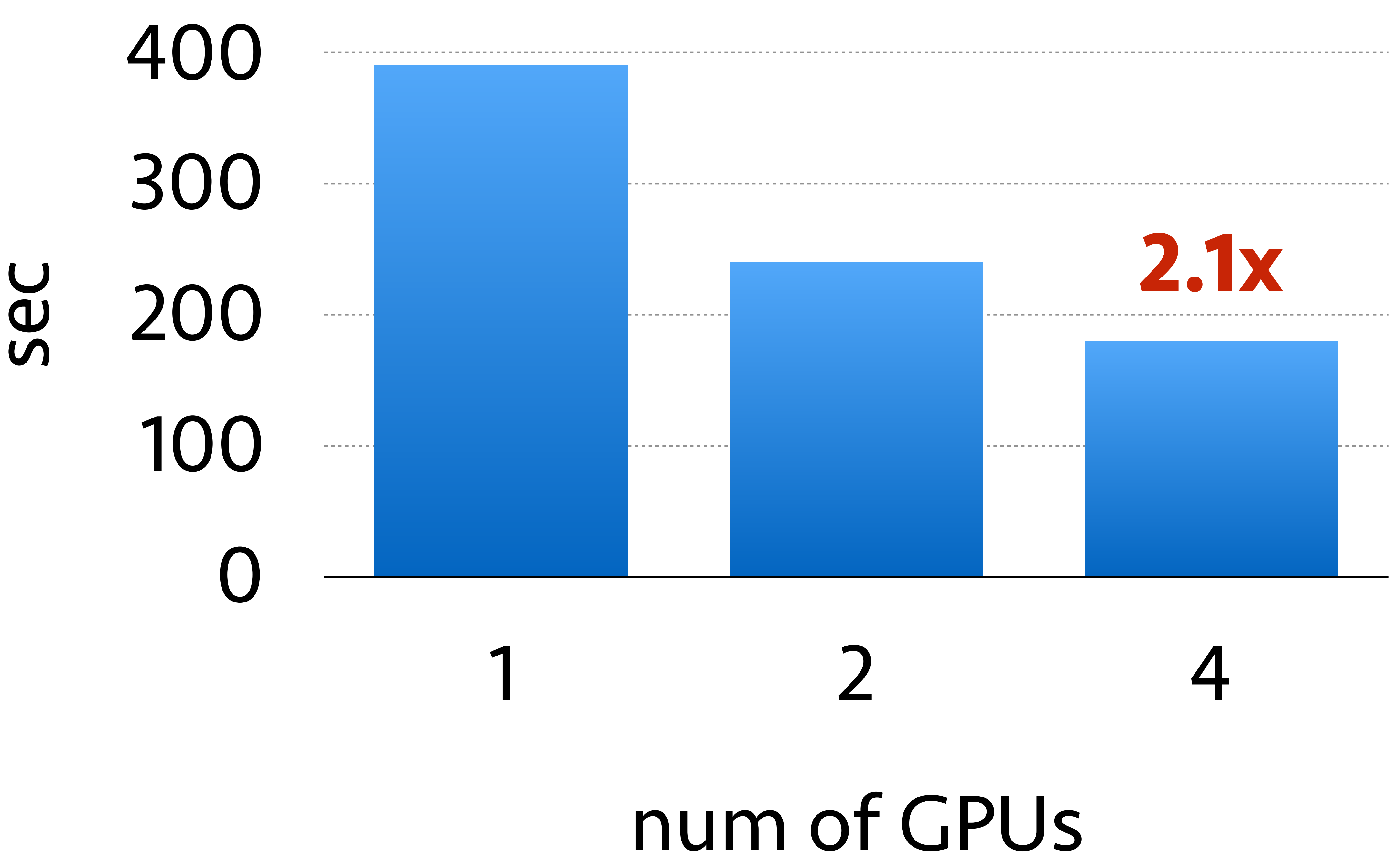


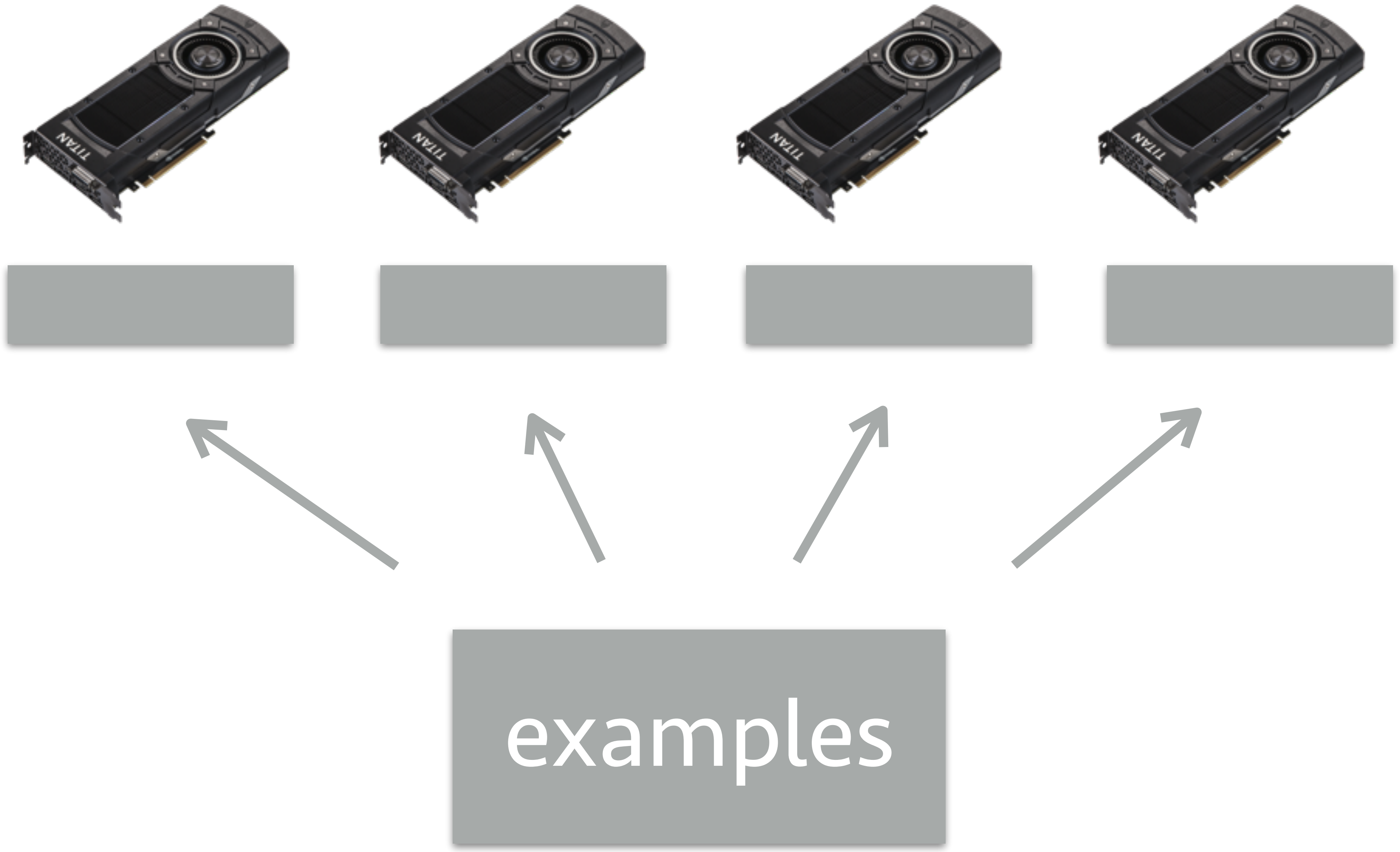
Time for one epoch on PTB:



Data Parallelism

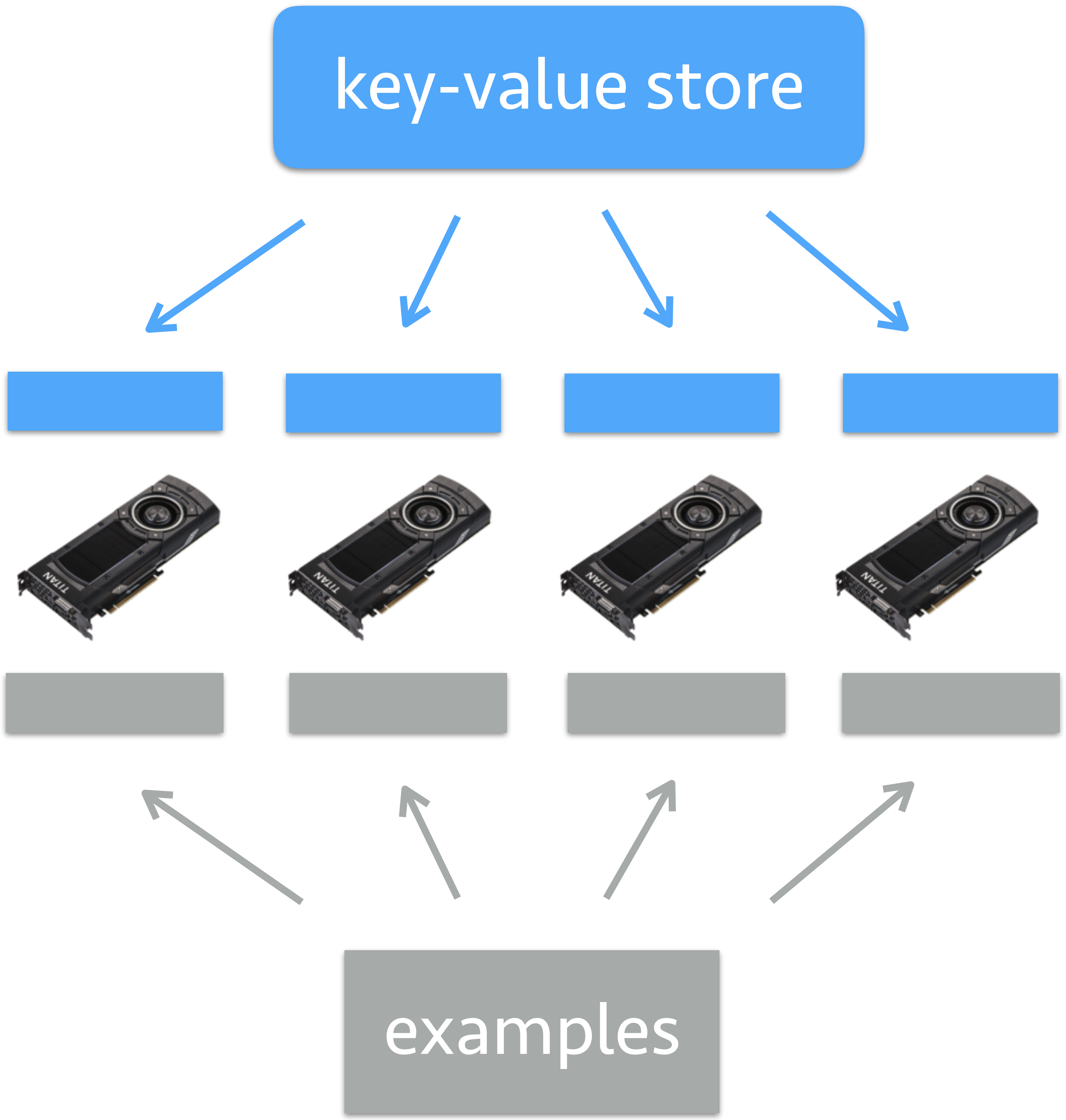
examples

Data Parallelism



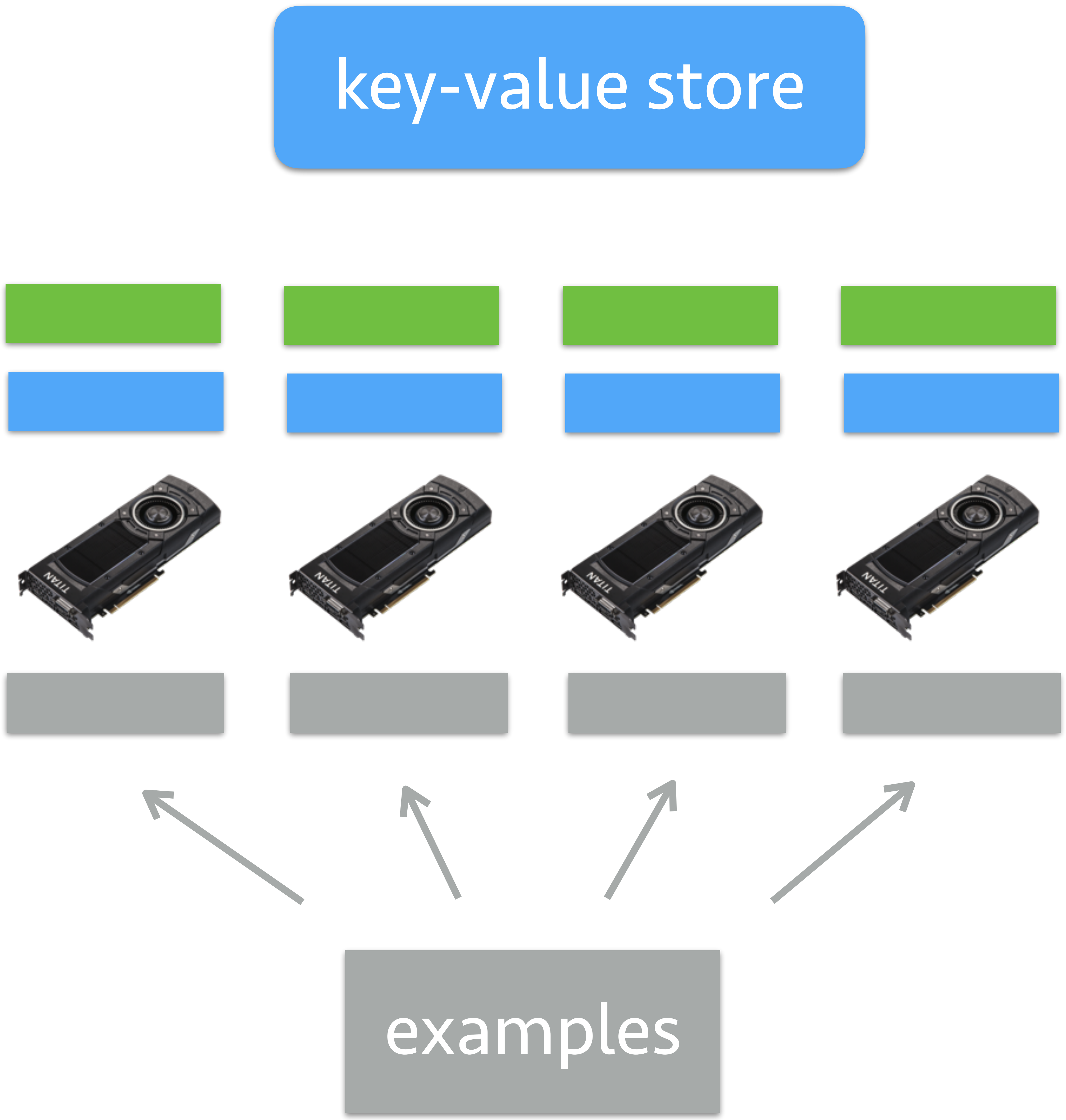
1. Read a data partition

Data Parallelism



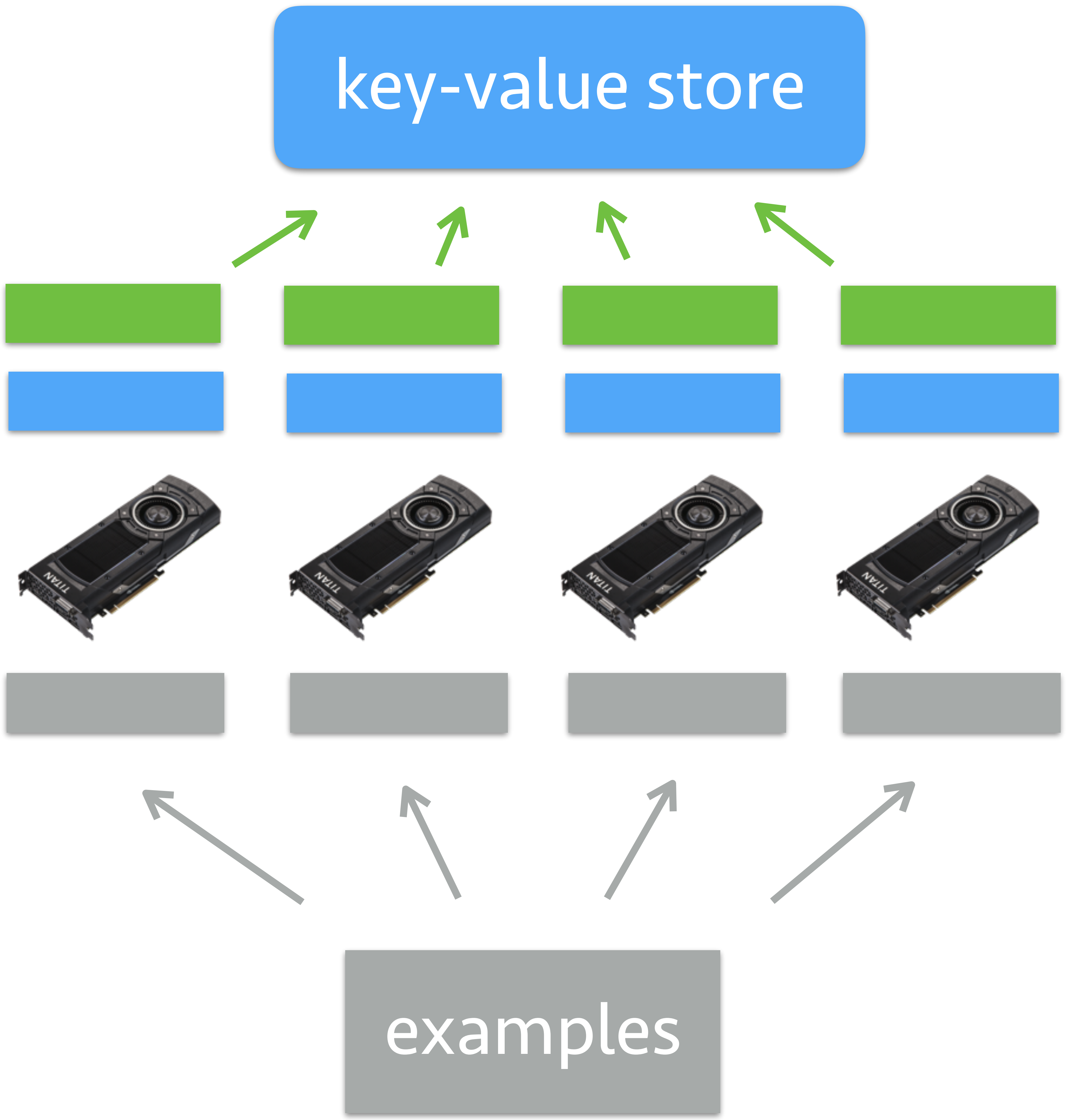
1. Read a data partition
2. Pull the parameters

Data Parallelism



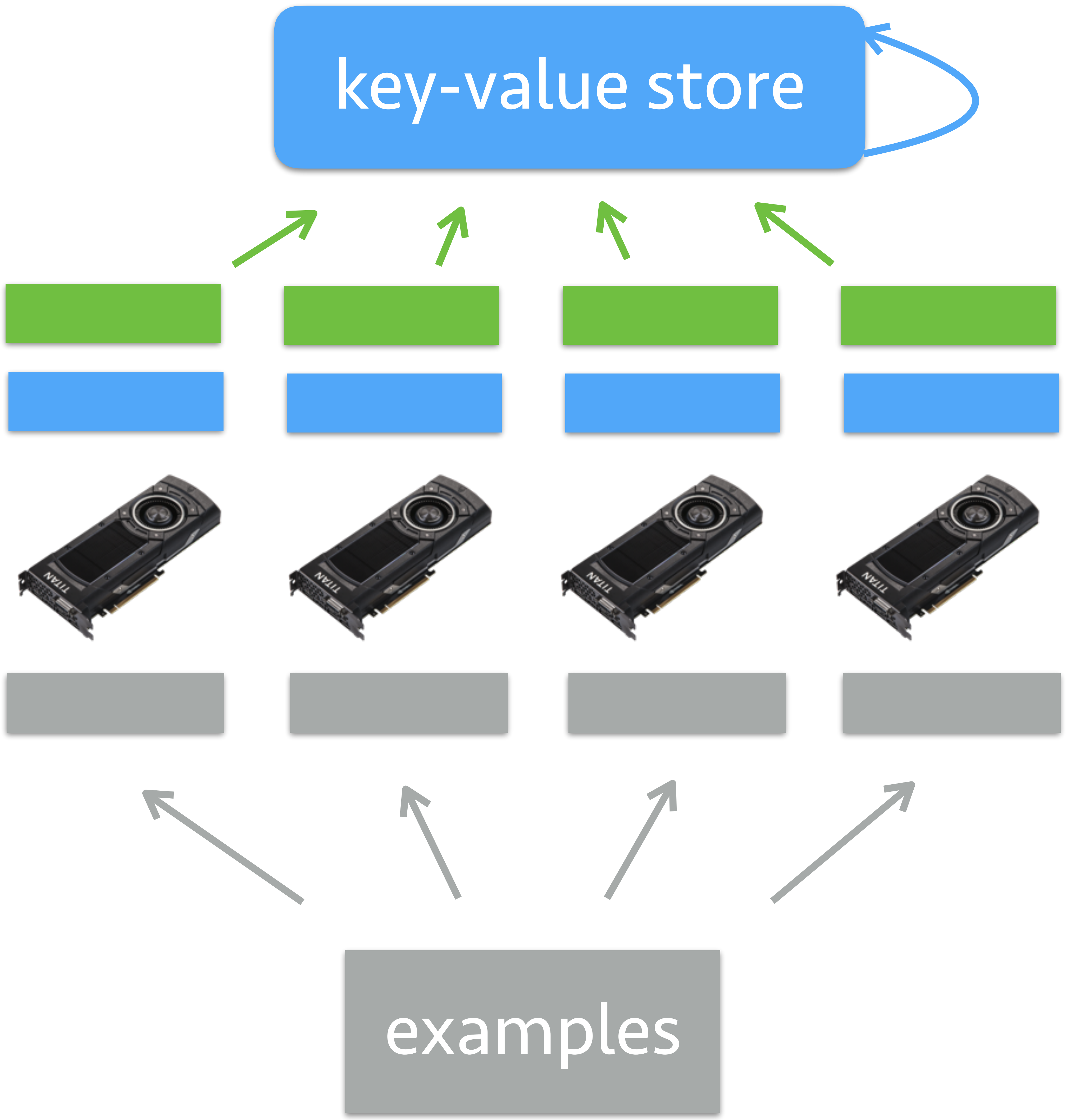
1. Read a data partition
2. Pull the parameters
3. Compute the gradient

Data Parallelism



1. Read a data partition
2. Pull the parameters
3. Compute the gradient
4. Push the gradient

Data Parallelism



1. Read a data partition
2. Pull the parameters
3. Compute the gradient
4. Push the gradient
5. Update the weight

Implementation

```
% create executor for each GPU
execs = [symbol.bind(mx.gpu(i)) for i in range(ngpu)]
% w -= learning_rate * grad
kvstore.set_updater(…)
% iterating on data
for dbatch in train_iter:
    % iterating on GPUs
    for i in range(ngpu):
        % read a data partition
        copy_data_slice(dbatch, execs[i])
        % pull the parameters
        for key in update_keys:
            kvstore.pull(key, execs[i].weight_array[key])
        % compute the gradient
        execs[i].forward(is_train=True)
        execs[i].backward()
        % push the gradient
        for key in update_keys:
            kvstore.push(key, execs[i].grad_array[key])
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automatic parallelism for mixed API

Results

- IMAGENET with 1.2m images and 1,000 classes
- 4 x Nvidia GTX 980
- Google Inception Network

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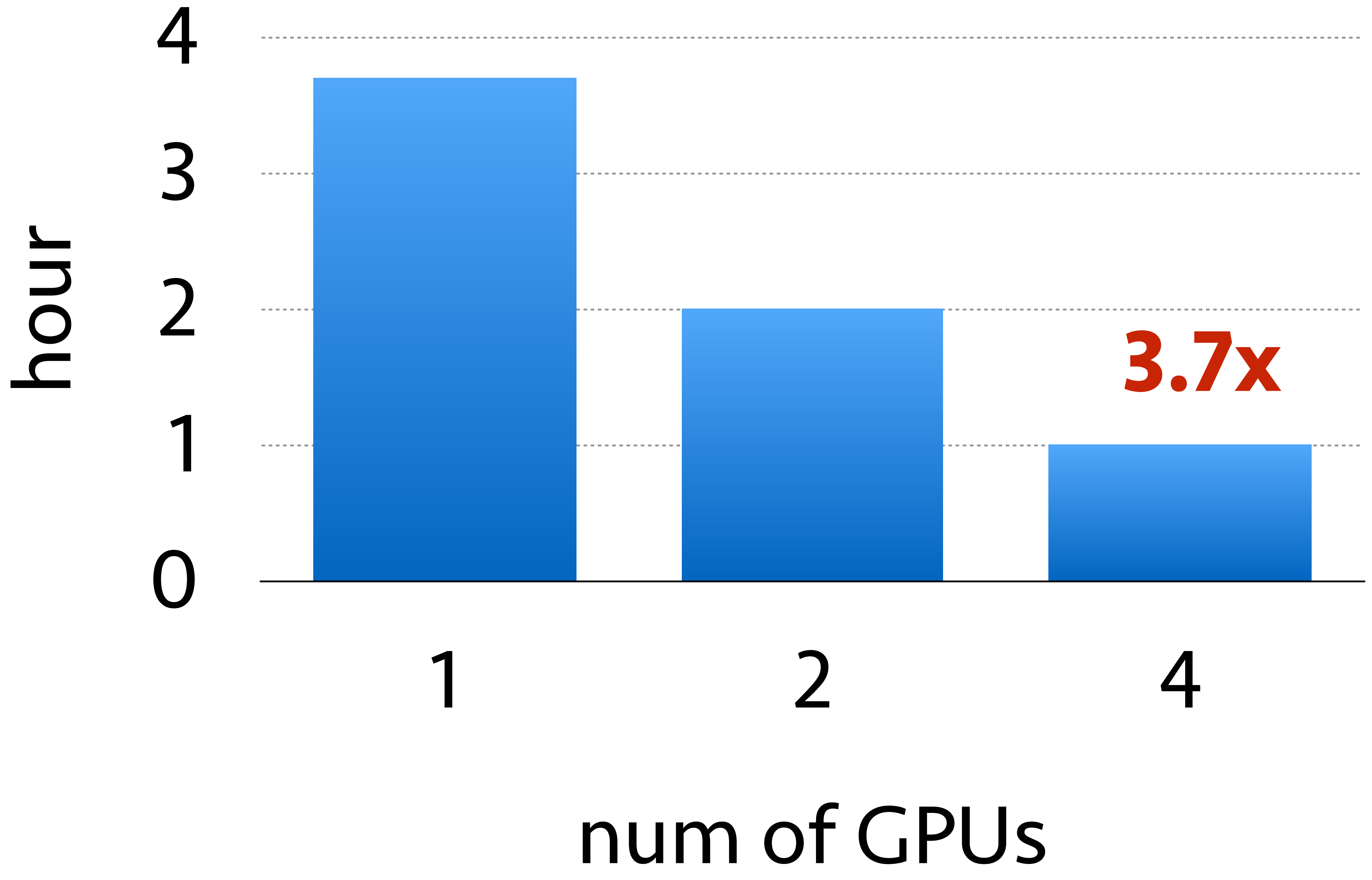


Distributed Computing

key-value store

examples

Distributed Computing

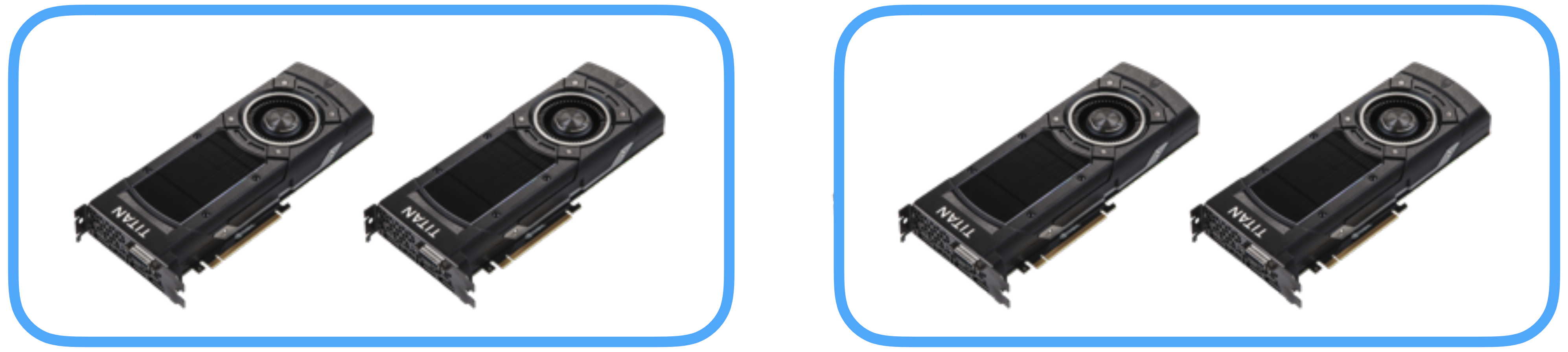
key-value store

examples

Store data in
a distributed filesystem

Distributed Computing

key-value store



multiple
worker machines

examples

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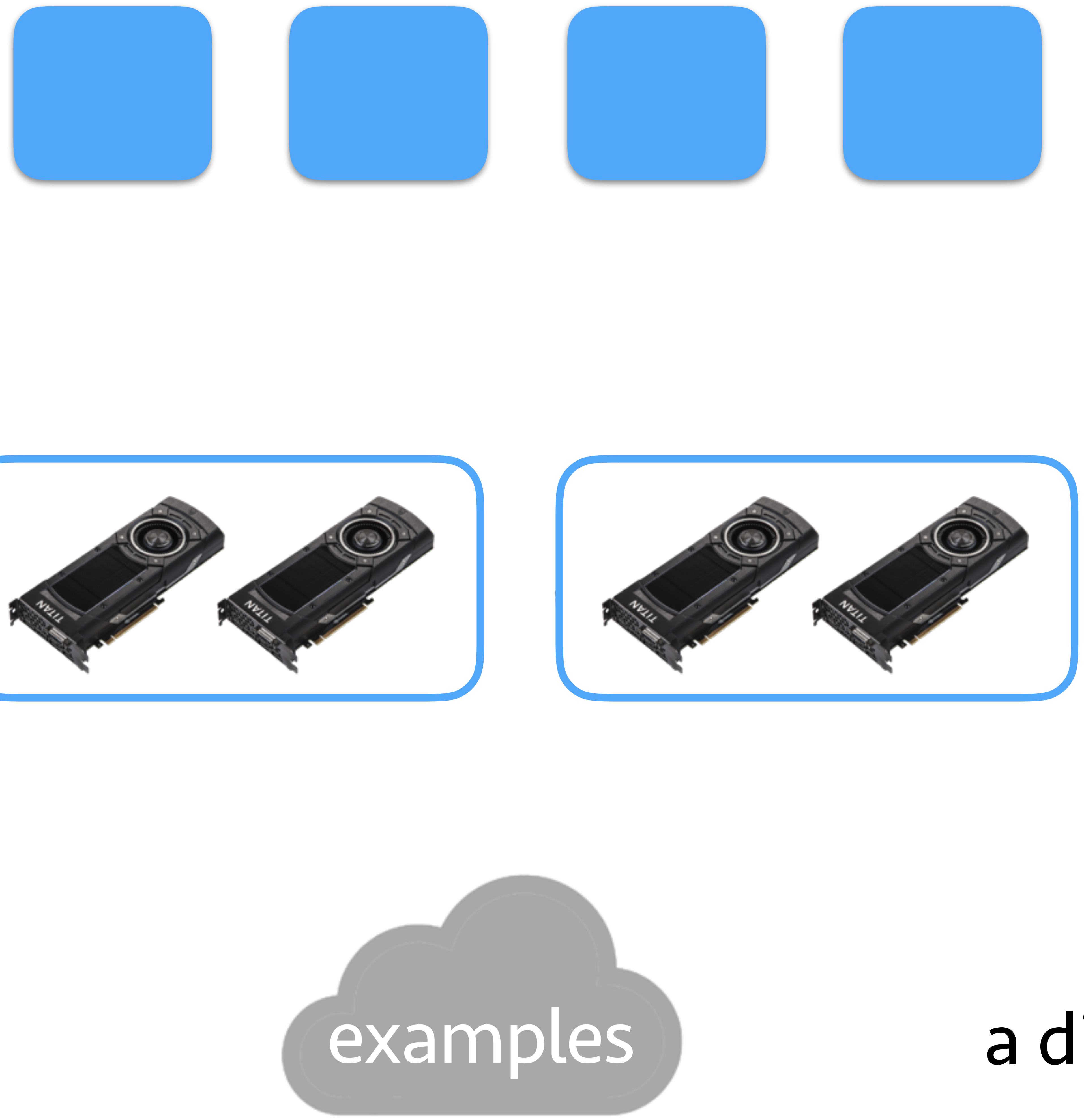
Distributed Computing



multiple
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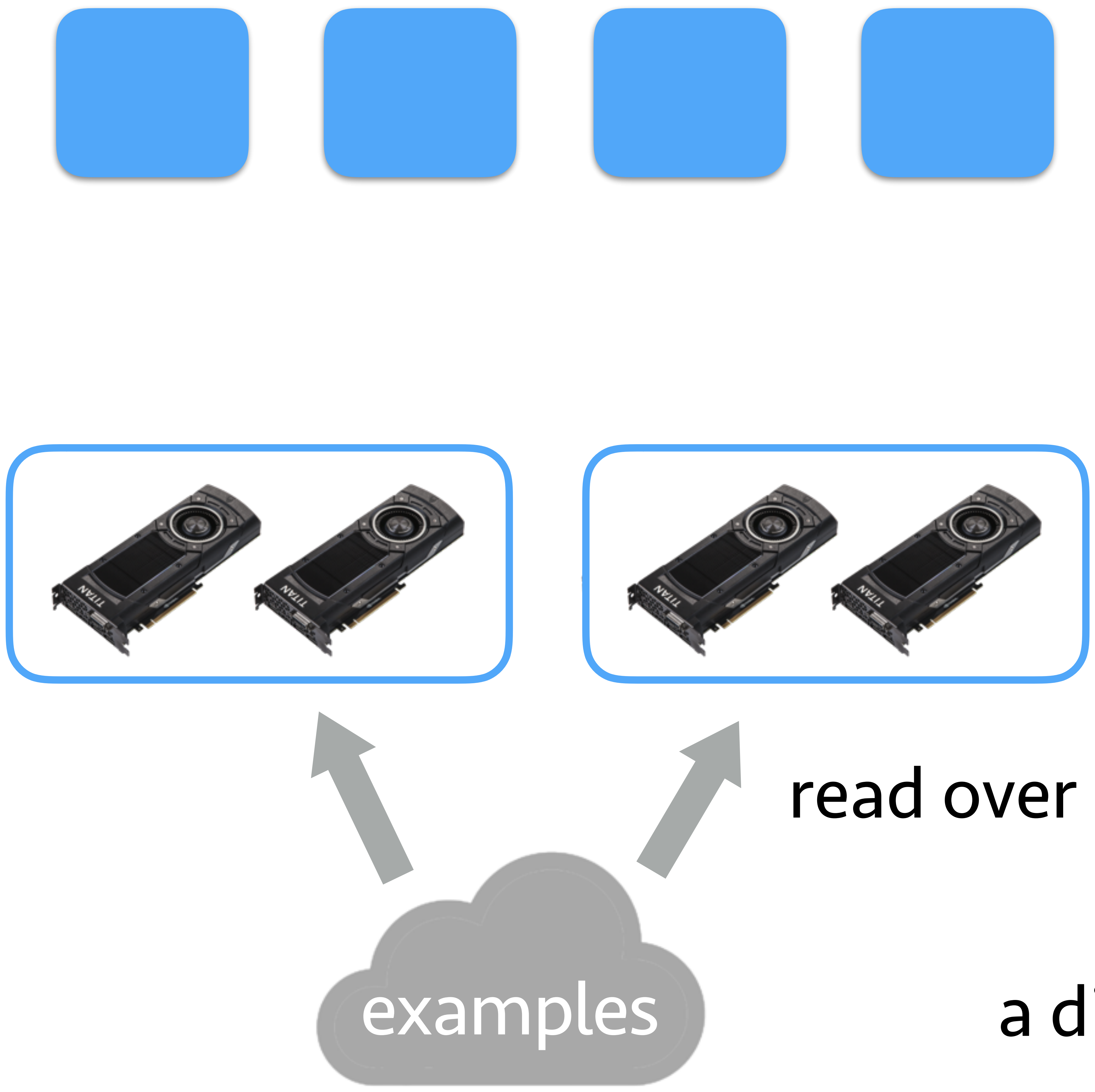
Distributed Computing



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read over network

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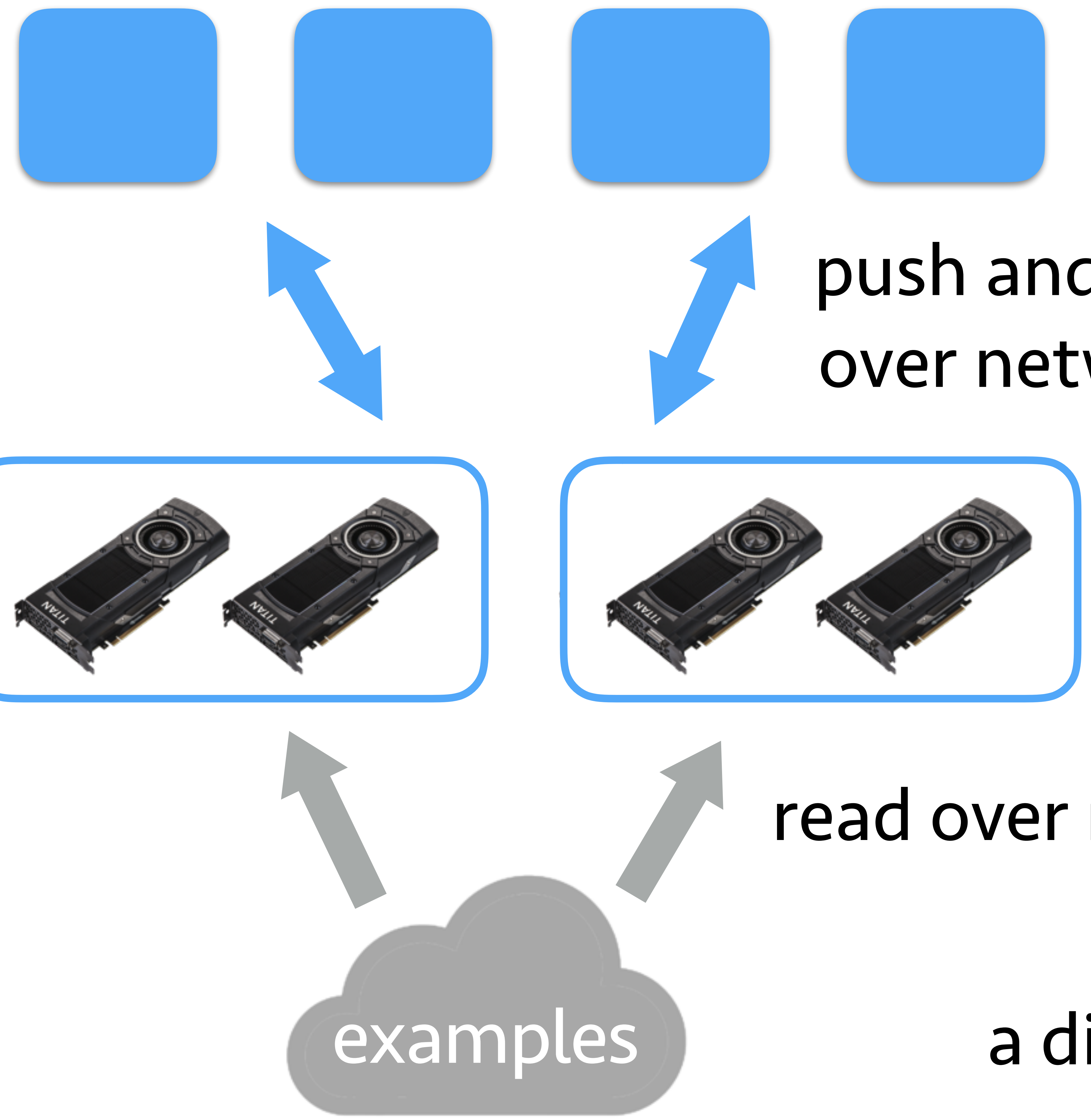

multiple
server machines

push and pull
over network

multiple
worker machines

read over network

Store data in
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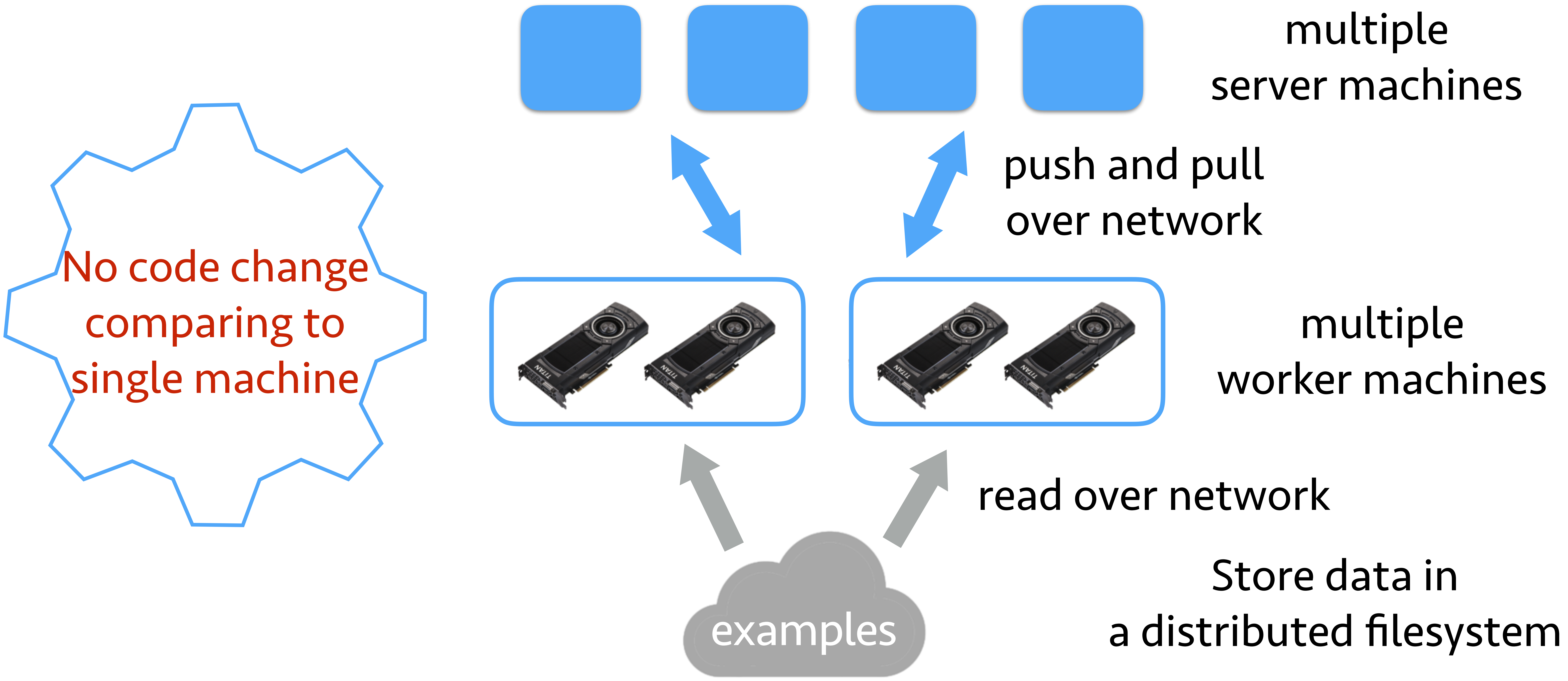
Distributed Computing



Distributed Experiments

- ImageNet with 1.2m images and 1,000 classes
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- Google Inception Network

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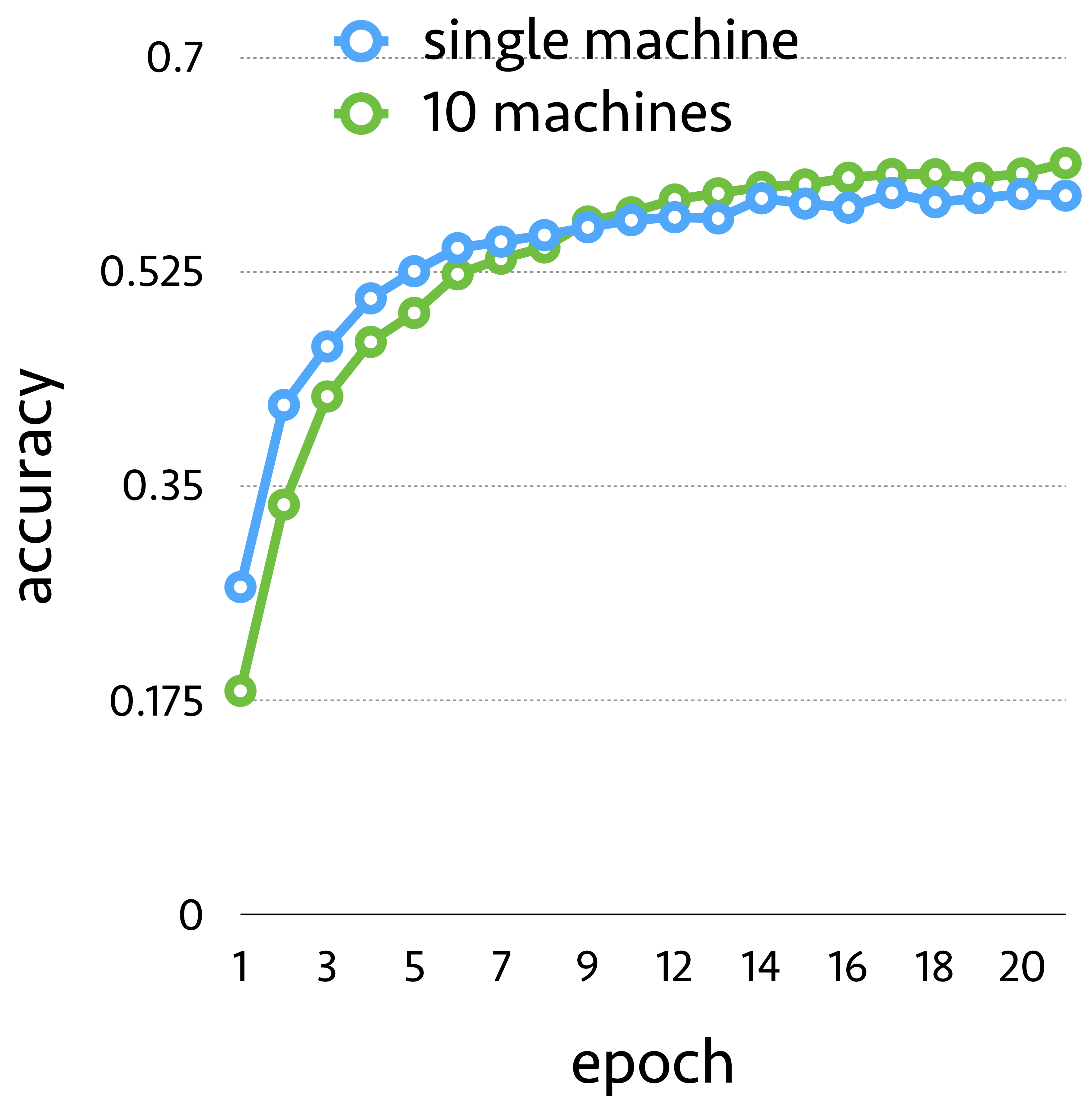
validation accuracy versus epoch



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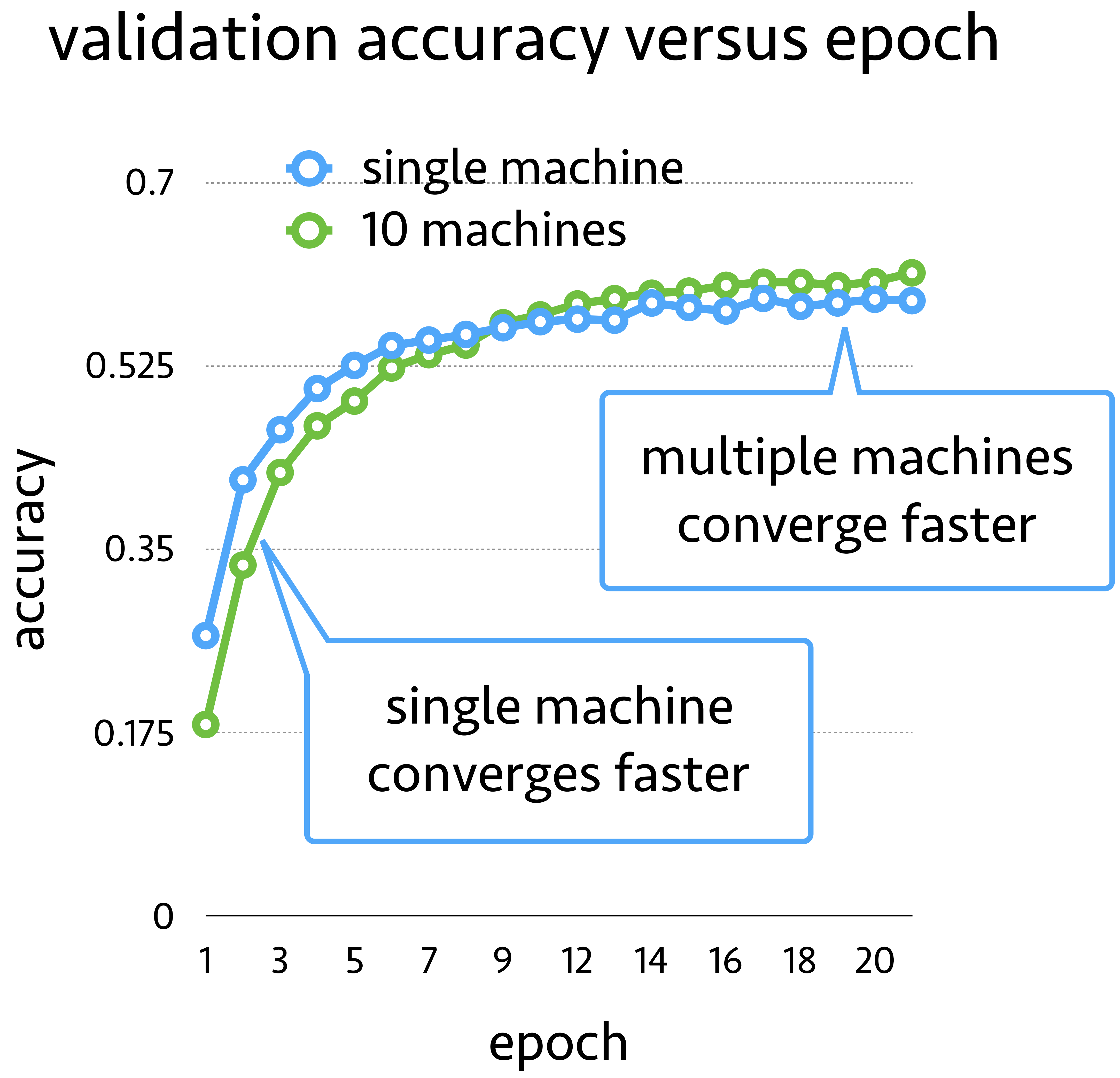

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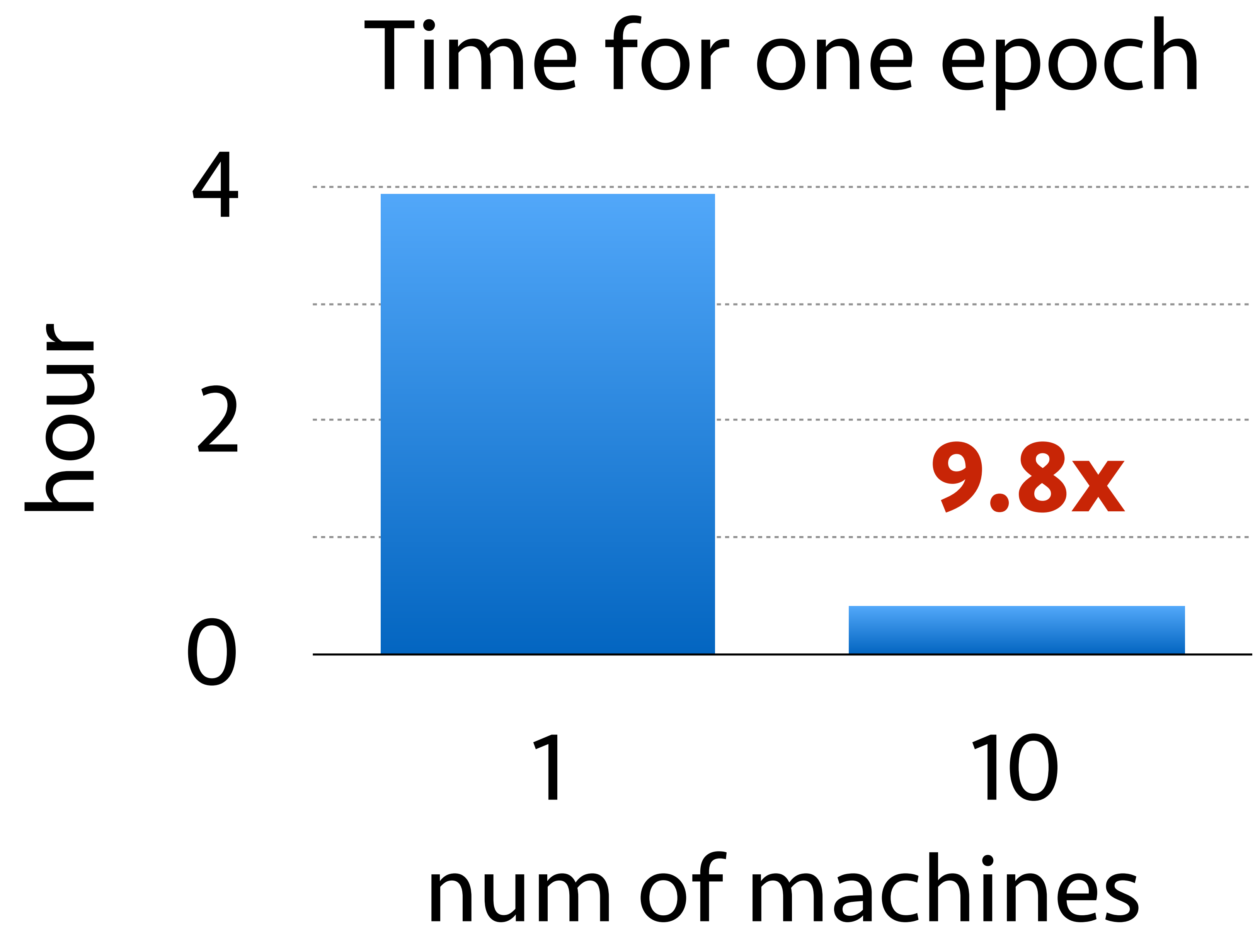

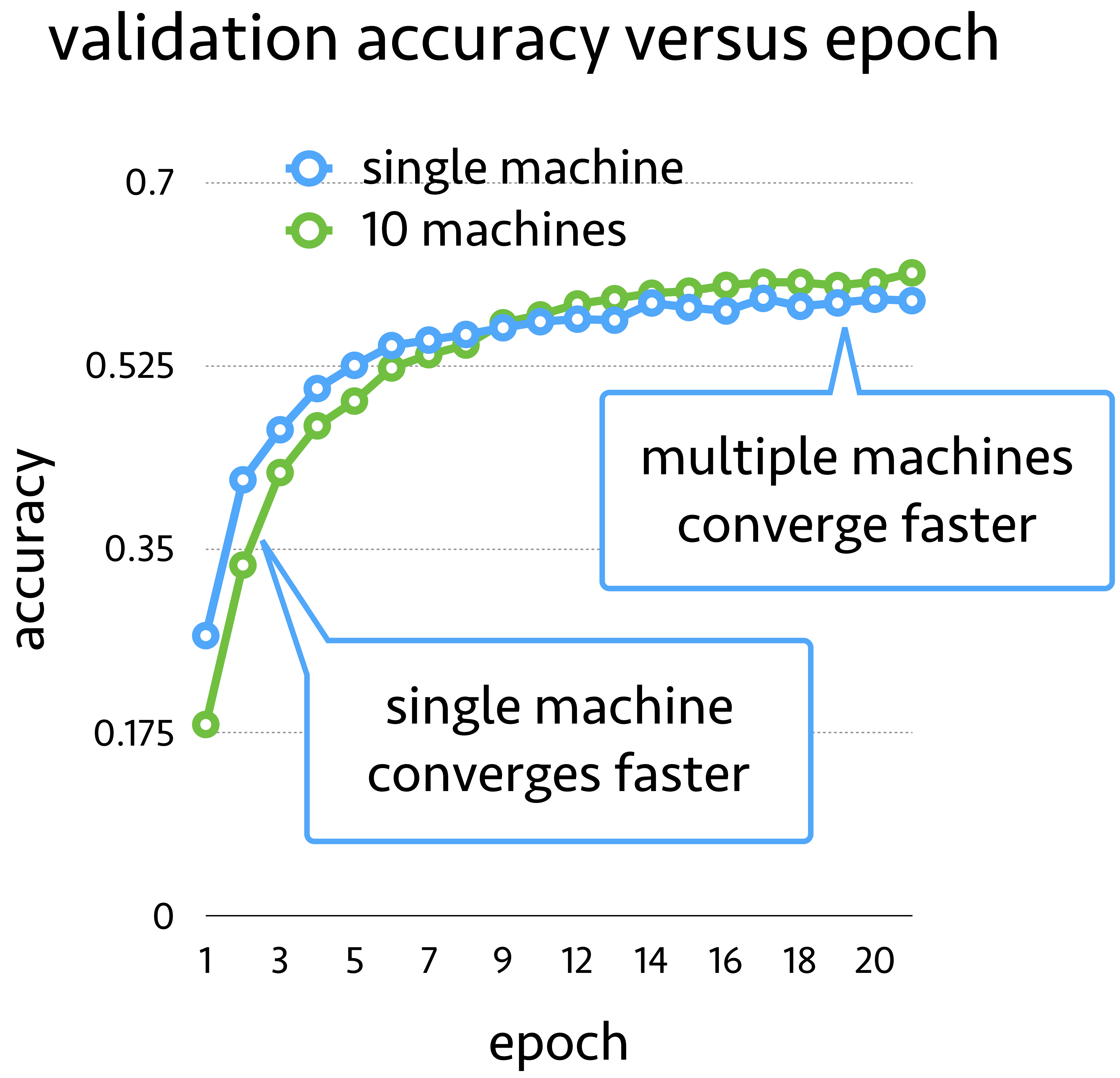

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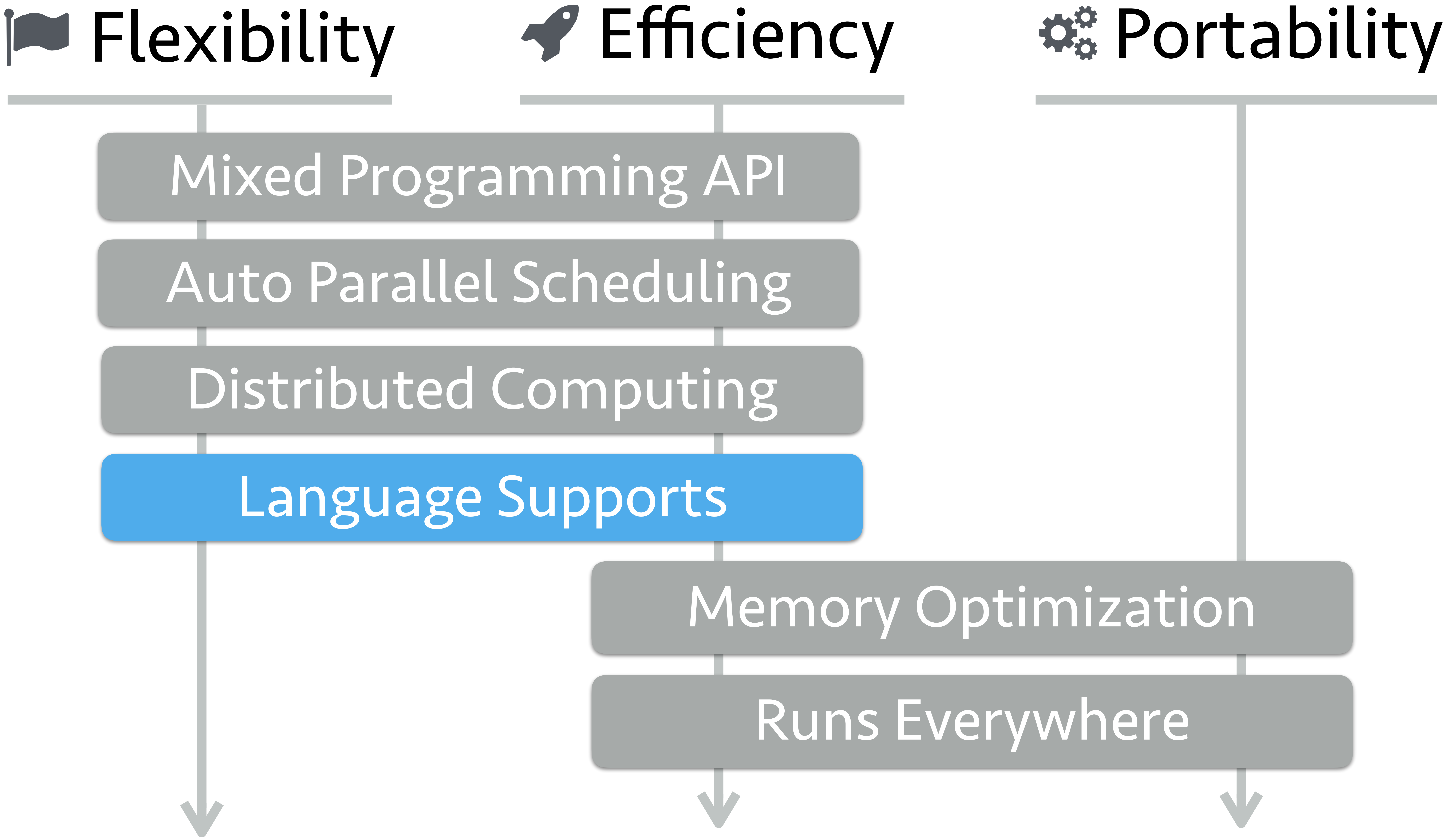

Multiple Languages

Multiple Languages

frontend

backend

Multiple Languages

frontend

backend

single implementation of backend system and common operators

performance guarantee regardless which frontend language is used

Minpy: MXNet Numpy Package

NumPy is the de facto scientific computing package in Python

Great flexibility (500+ operators) but CPU-only

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- Native Numpy Integration

```
>>> import numpy as np   ⇨   >>> import minpy as np
```

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Great flexibility (500+ operators) but CPU-only

- Native Numpy Integration

```
>>> import numpy as np   ⇨   >>> import minpy as np
```

- Transparent CPU and GPU co-execution

```
>>> x = np.zeros((10, 20)) # call GPU function
>>> y = np.sort(x)         # call CPU function; copy GPU->CPU
>>> z = np.log(y)          # call GPU function; copy CPU->GPU
```

Minpy: MXNet Numpy Package

- Small operators (Numpy) + Big operators (MXNet)

```
>>> symbol = mx.symbol.FullyConnected(…)
>>> bigop = minpy.core.function(sigmoid, …)
>>> def training_loss(w, x, y):
...     pred = bigop(input=x, fc_weight=w)
...     prob = pred * y + (1 - pred) * (1 - y)
...     return -np.sum(np.log(prob))
```

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```

- Imperative style auto-differentiation

```
>>> grad_func = minpy.core.grad_and_loss(train_loss)
>>> dw = grad_fn(w, x, y)
```

Bring Torch to MXNet

Torch is a popular Lua framework for
both scientific computing and deep learning

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both scientific computing and deep learning

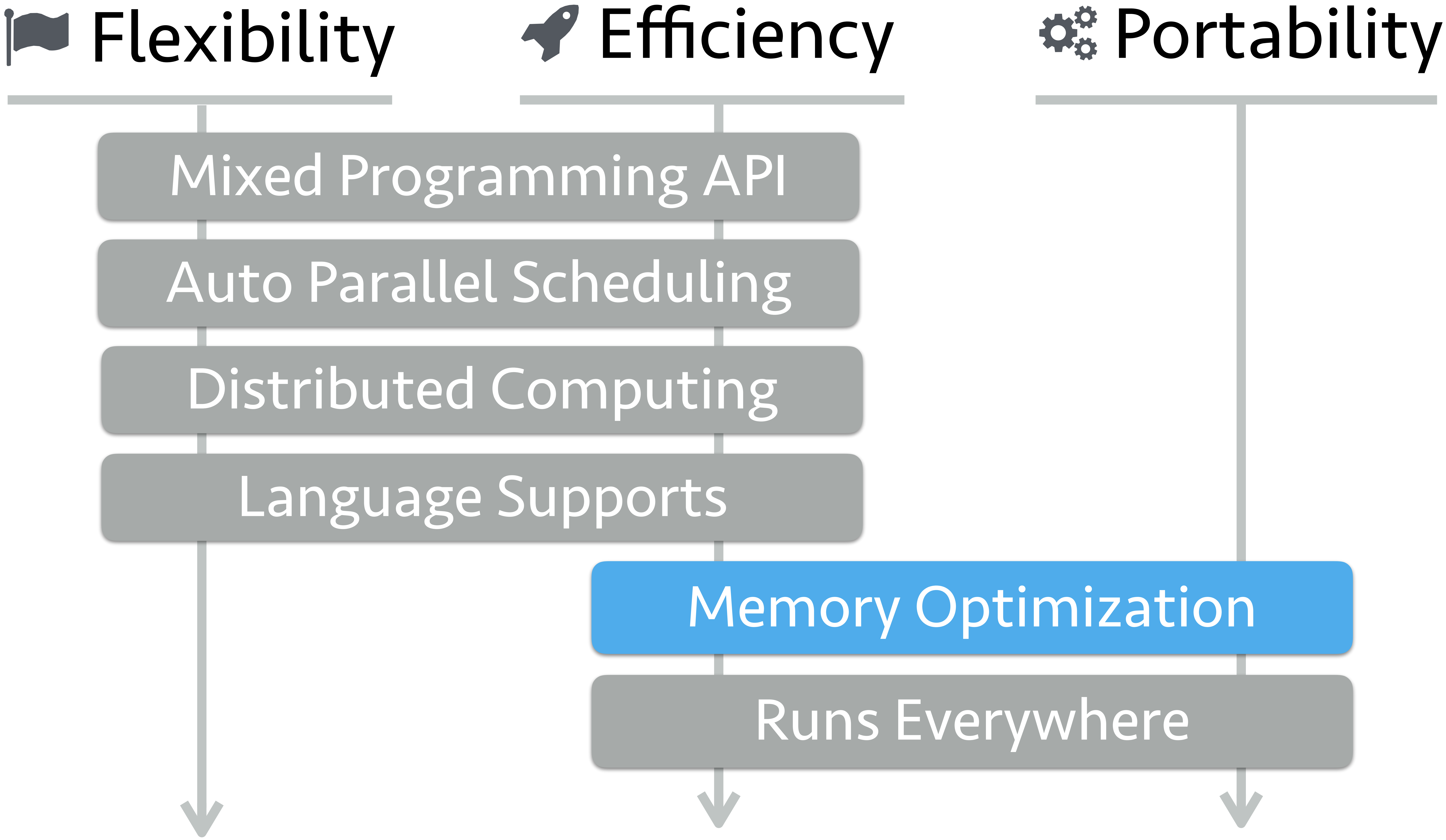
- Tensor Computation

```
>>> import mxnet as mx
>>> x = mx.th.randn(2, 2, ctx=mx.gpu(0))
>>> y = mx.th.abs(x)
>>> print y.asnumpy()
```

- Modules (Layers)

```
>>> import mxnet as mx
>>> data = mx.symbol.Variable(‘data’)
>>> fc   = mx.symbol.TorchModule(data_0=data,
...                              lua_string=‘nn.Linear(784, 128)’,…
>>> mlp  = mx.symbol.TorchModule(data_0=fc,
...                              lua_string=‘nn.LogSoftMax()’,…
```

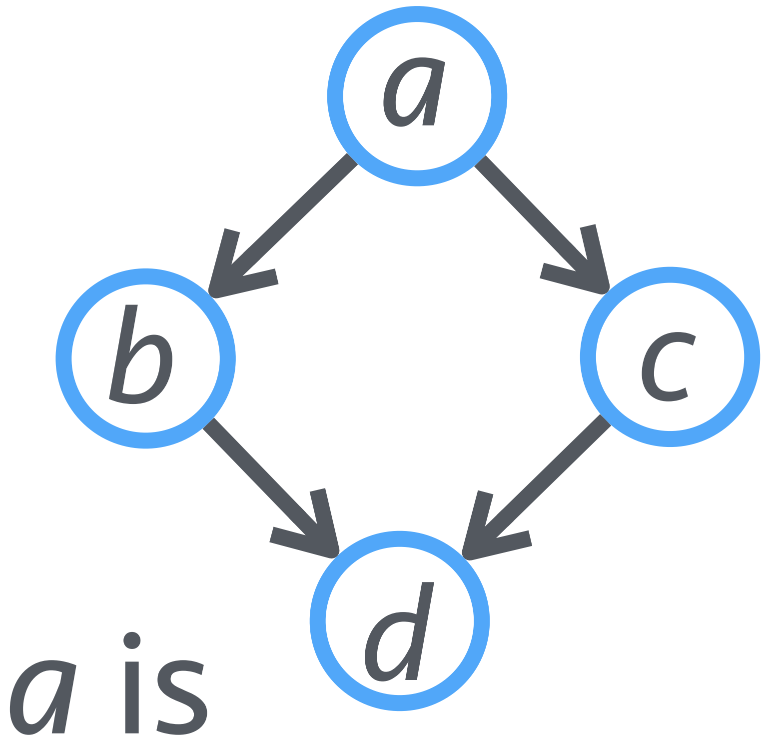
MXNet Highlights



Memory Optimization

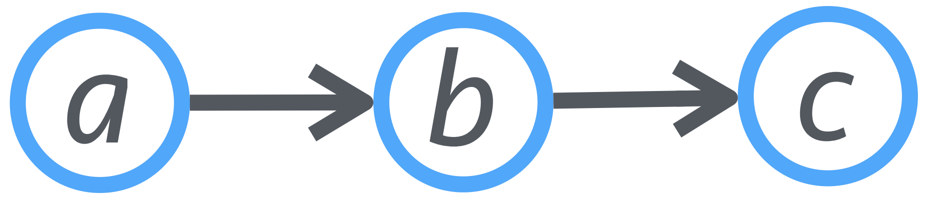
Traverse the computation graph to reduce the memory footprint with linear time complexity

aliveness analysis



now *a* is deletable

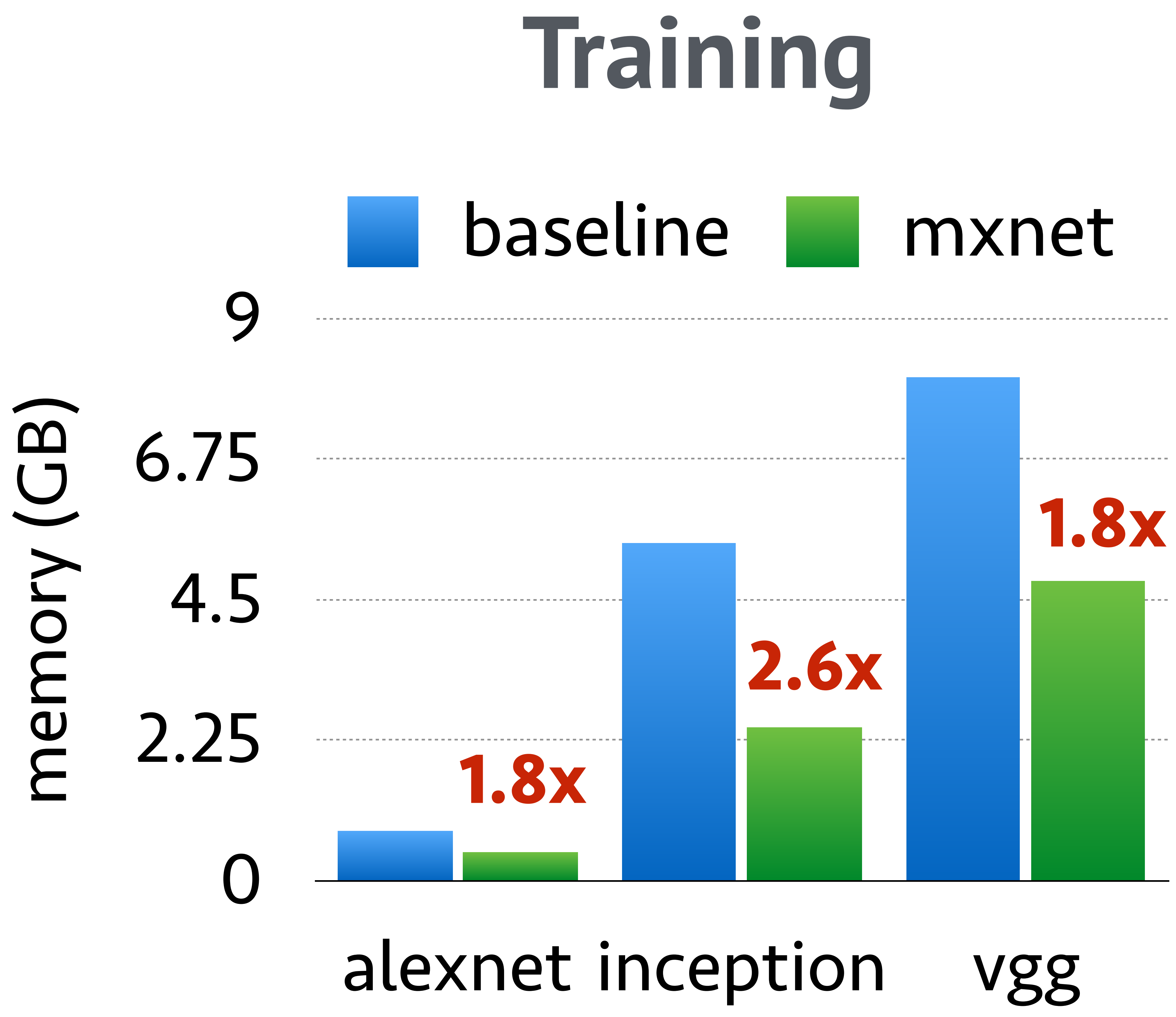
shared space between variables

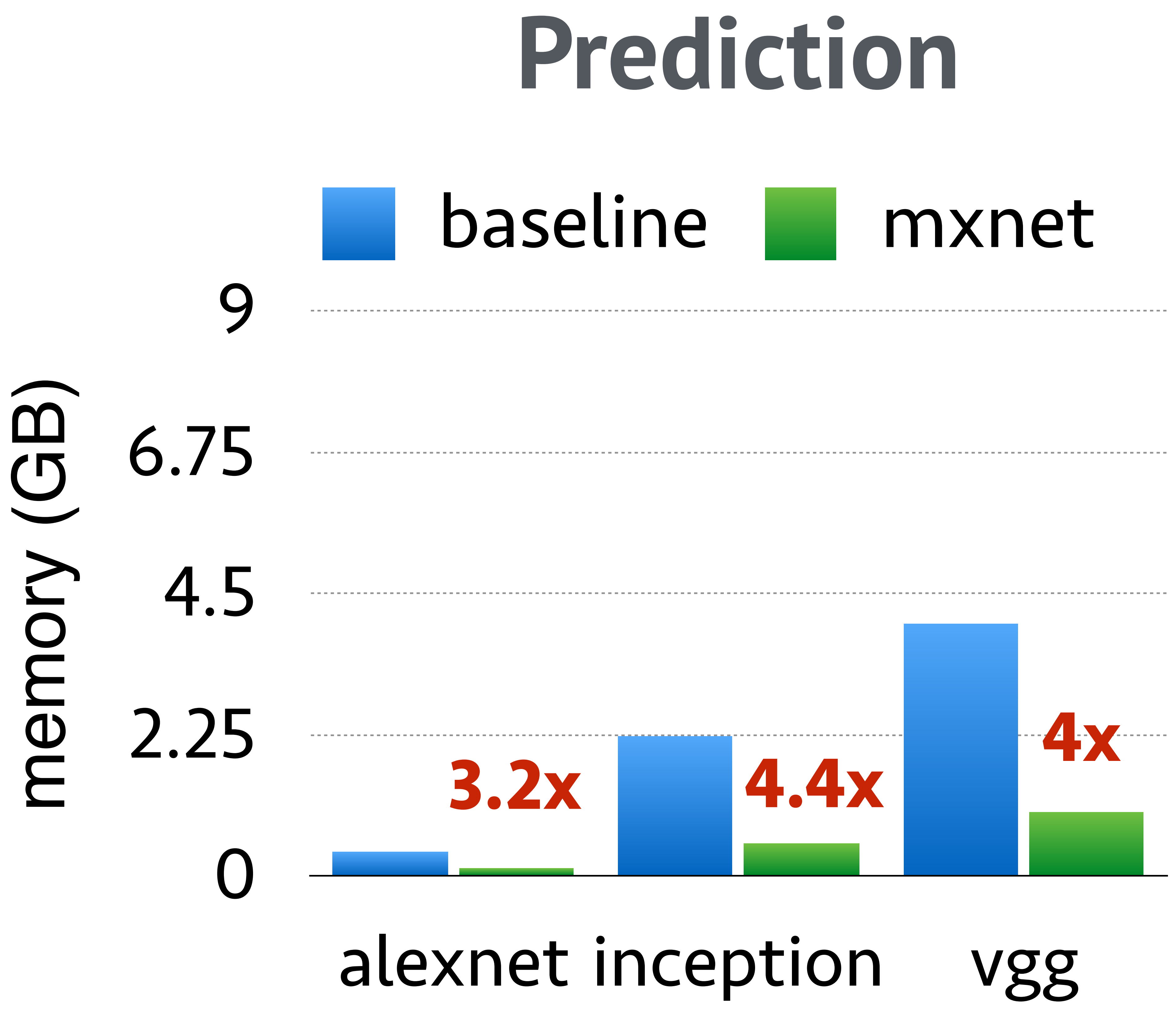


share *a* and *b*

Results for Deep CNNs

IMAGENET winner neural networks



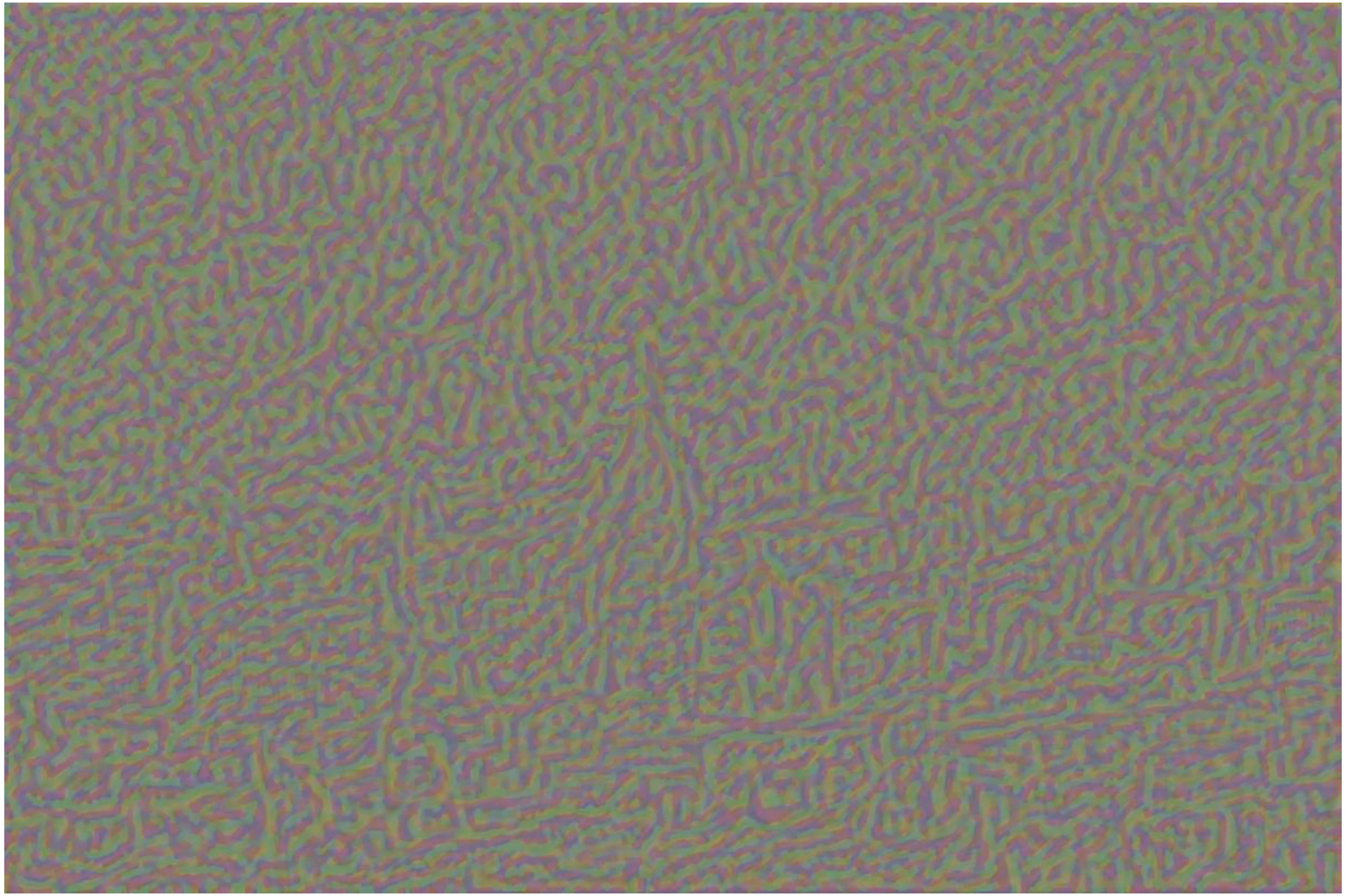


Neural Art

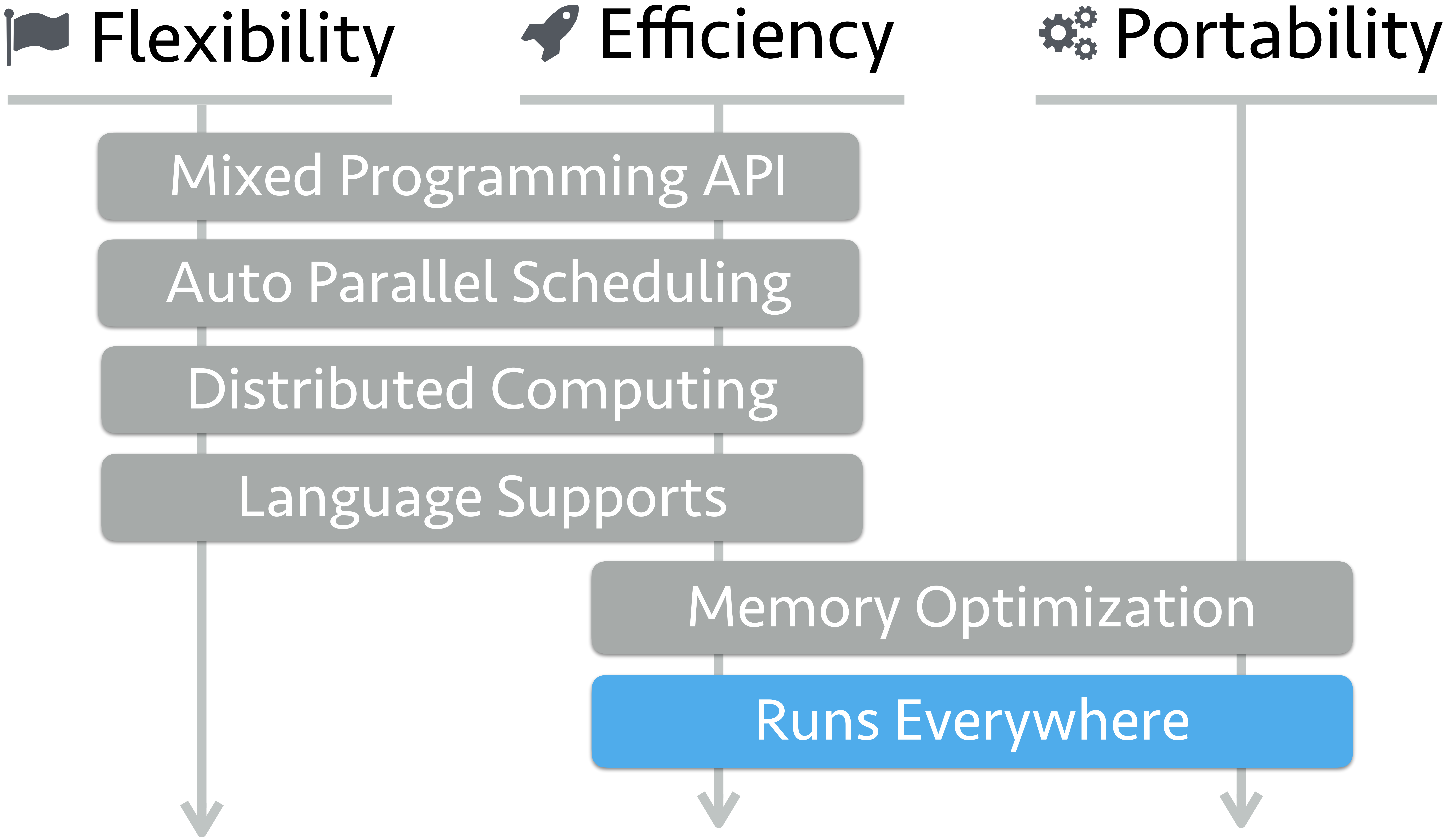
Neural Art

1M pixels
GTX 980 TI 6G

in 20x speed



MXNet Highlights



Train on the Cloud

Consume data from
distributed filesystems

HDFS

S3

Blob

⋮

multithreaded read/write
to hide network latency

Train on the Cloud

Consume data from distributed filesystems

HDFS

S3

Blob

⋮

multithreaded read/write to hide network latency

Launch distributed jobs

SSH

MPI

qsub

Yarn

⋮

easily extend to other cluster resource management software

Deploy Everywhere

Beyond

Deploy Everywhere

Beyond

Amalgamation

- Fit the core library with all dependencies into a single C++ source file
- Easy to compile on ...

Deploy Everywhere

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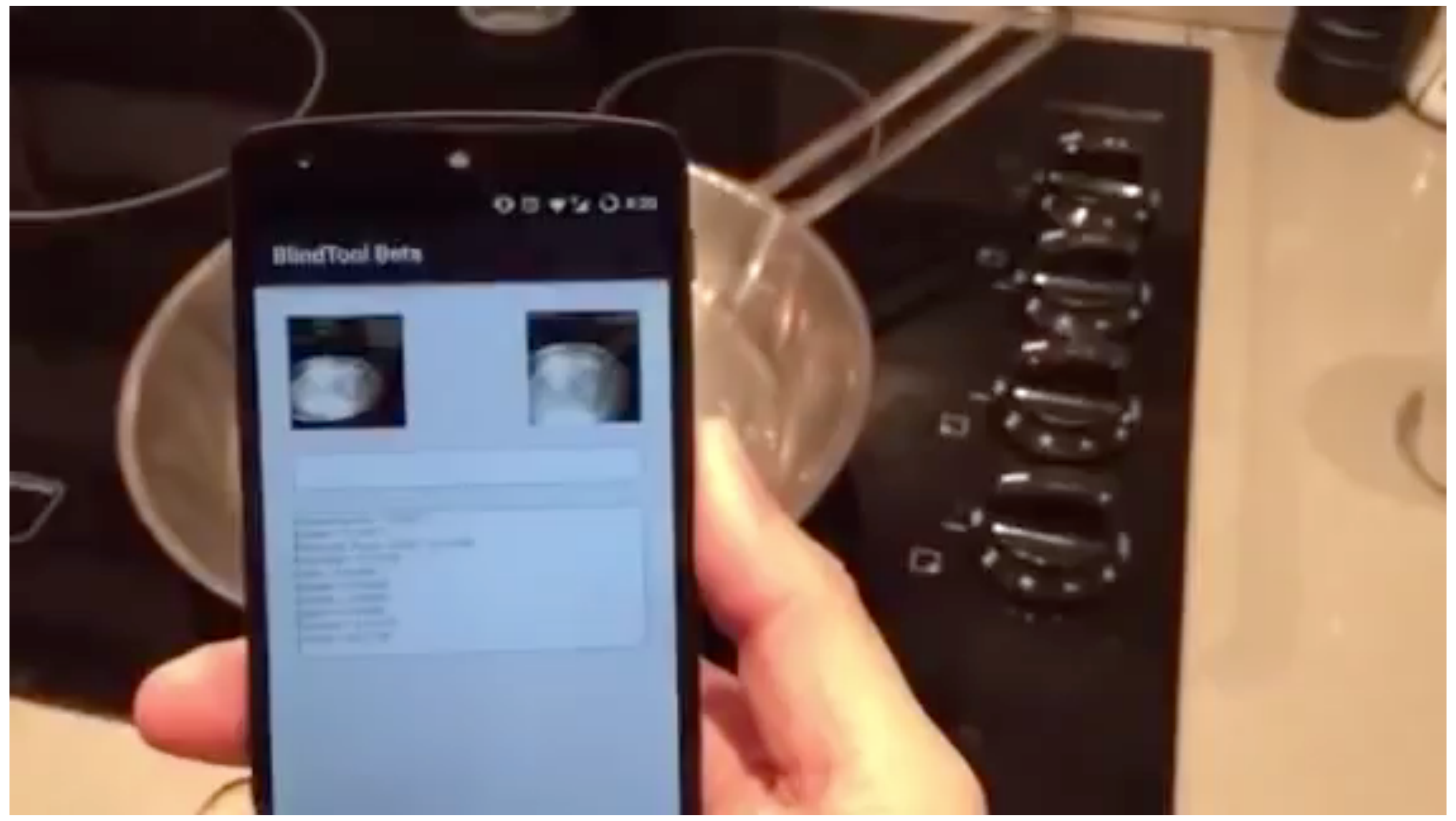

BlindTool by Joseph Paul Cohen, demo on Nexus 4

Deploy Everywhere

Beyond

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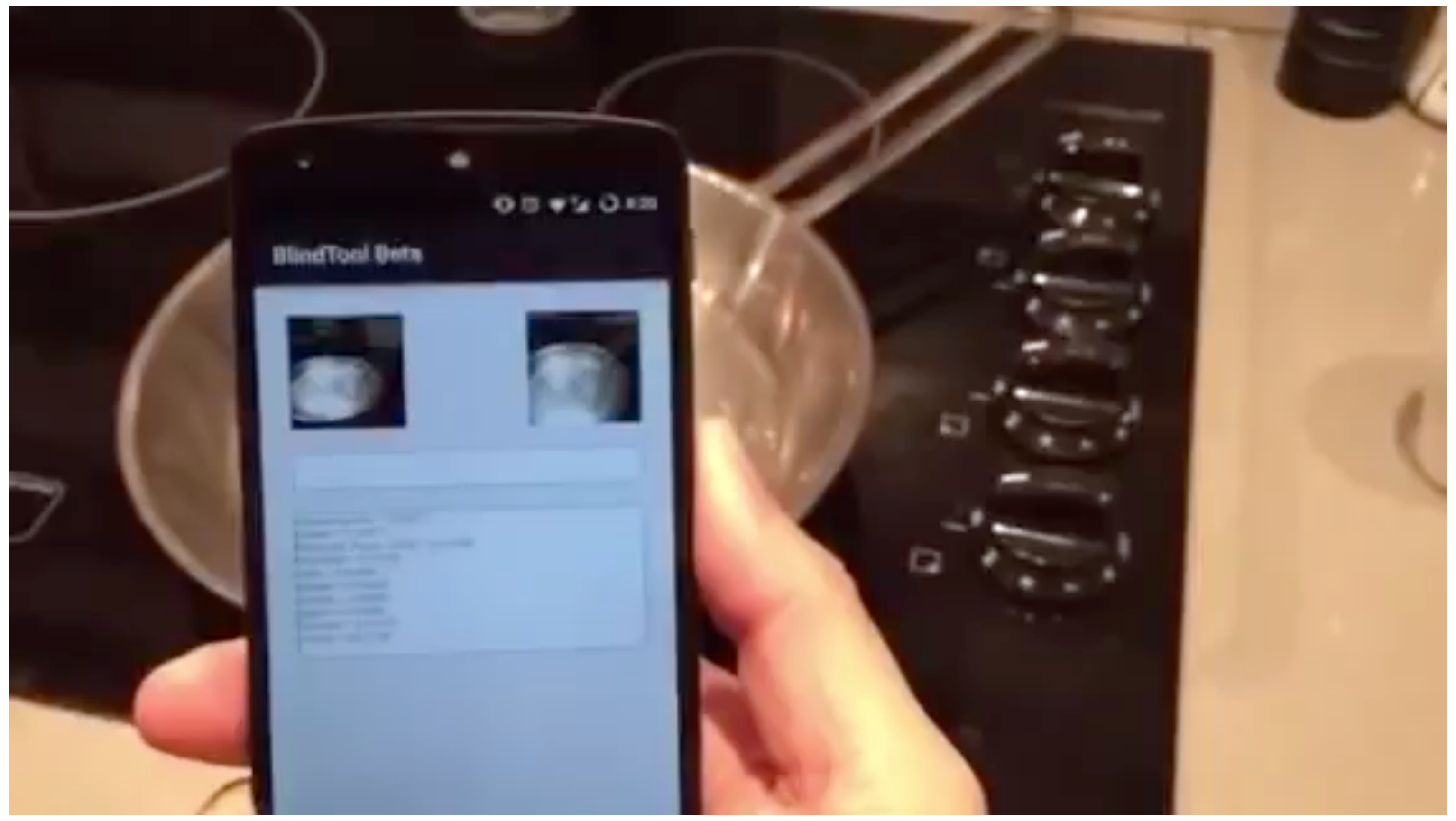

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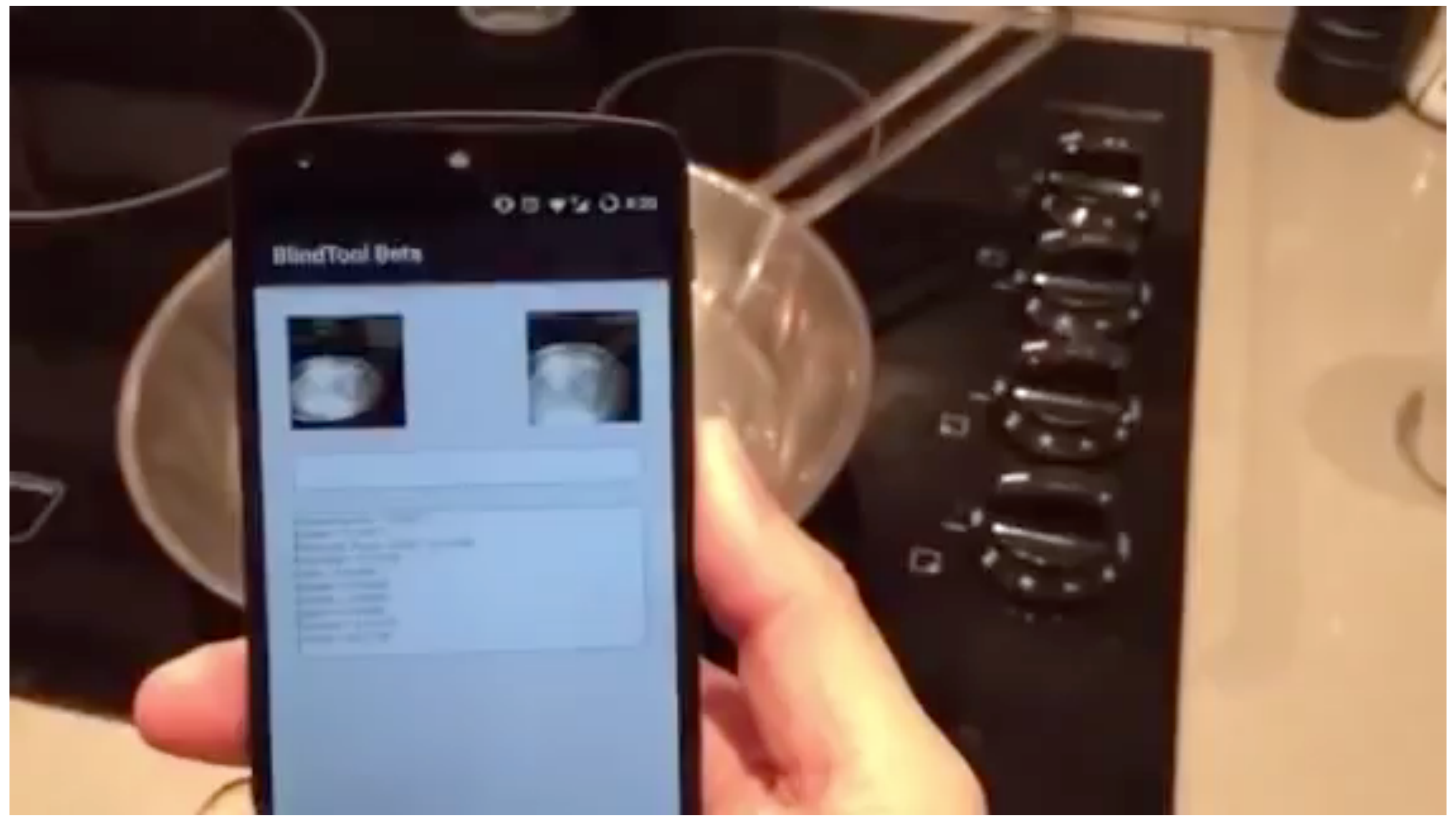

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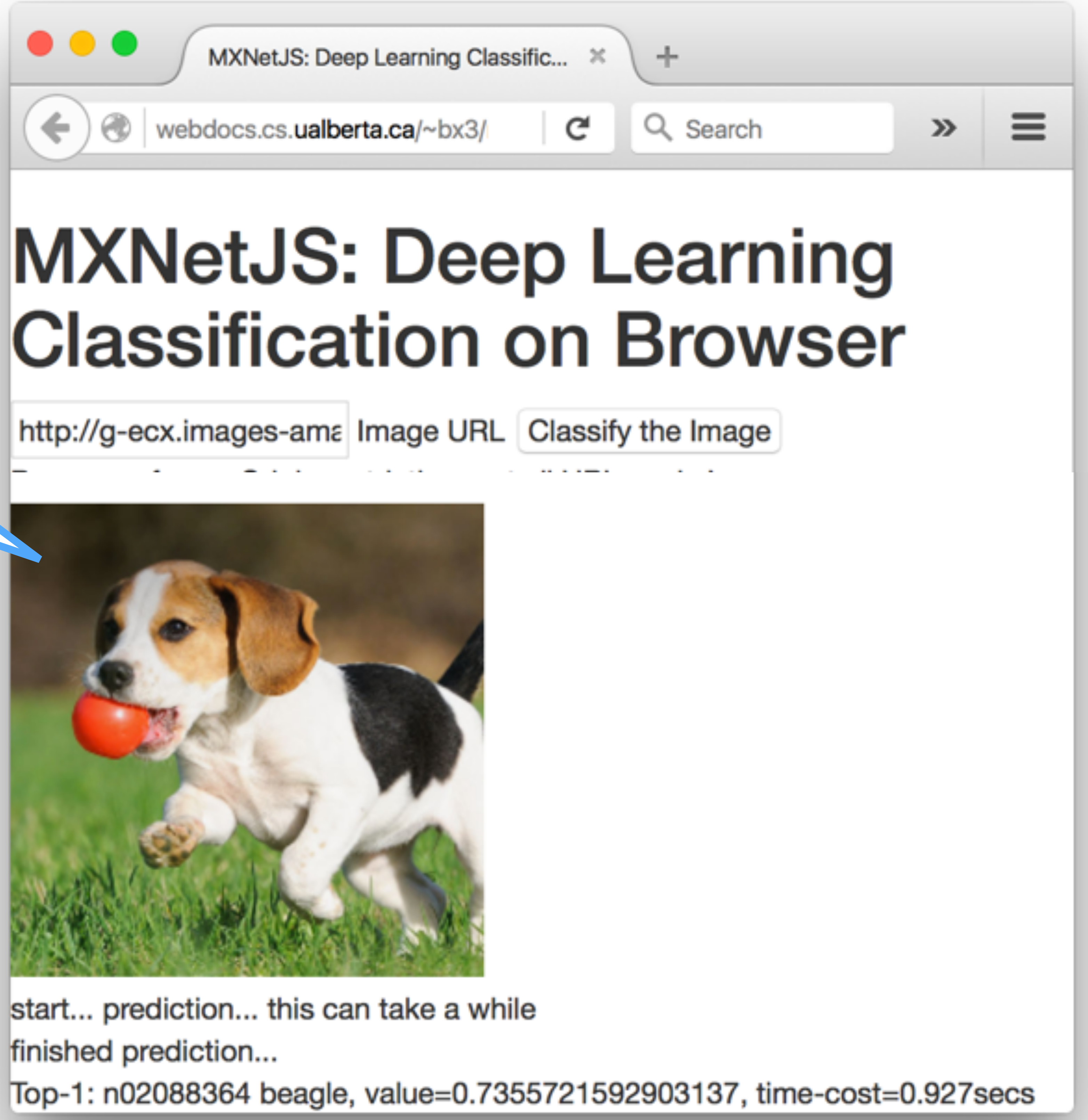
The first image for search "dog" at images.google.com



Deploy Everywhere

Beyond

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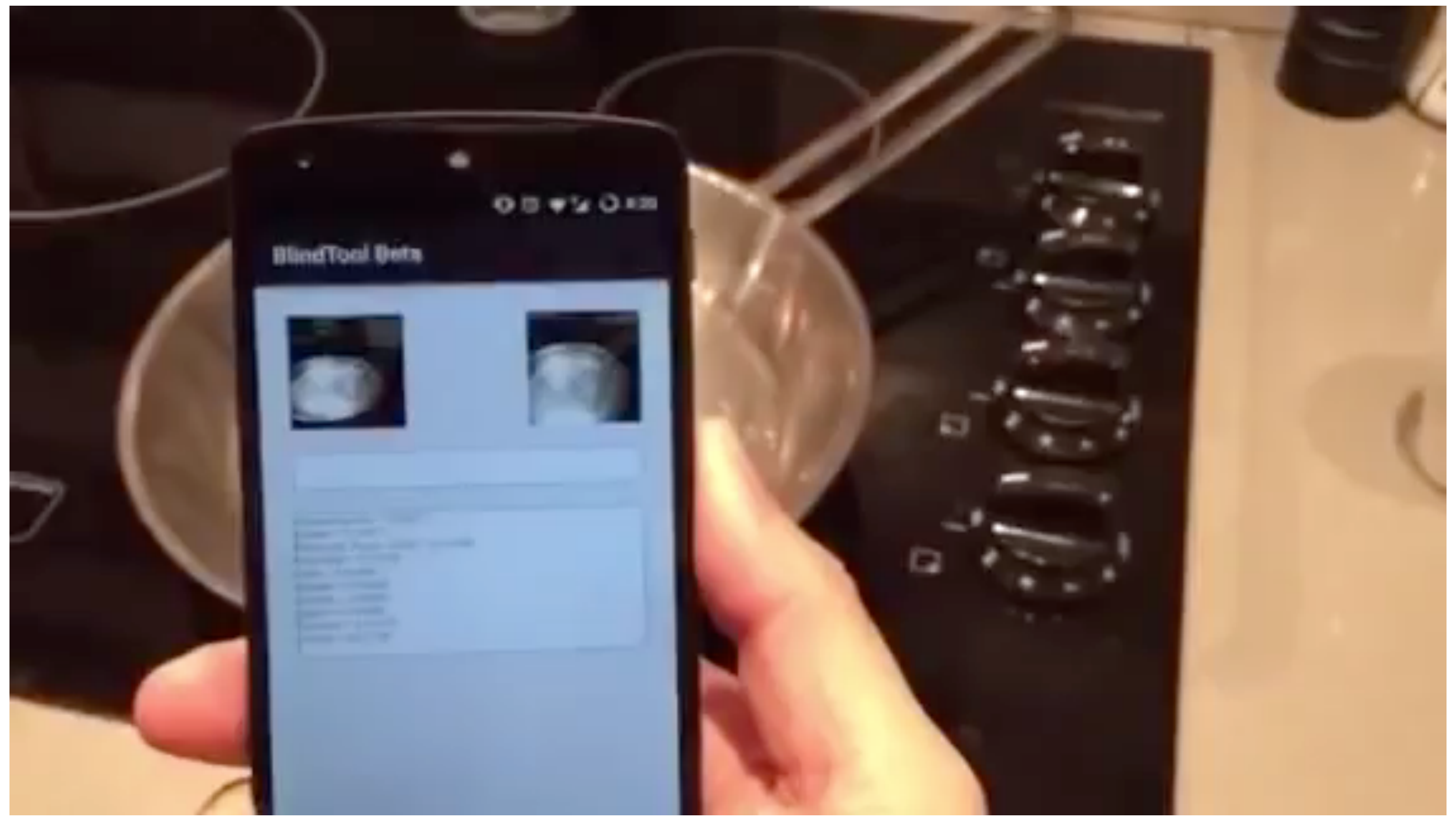

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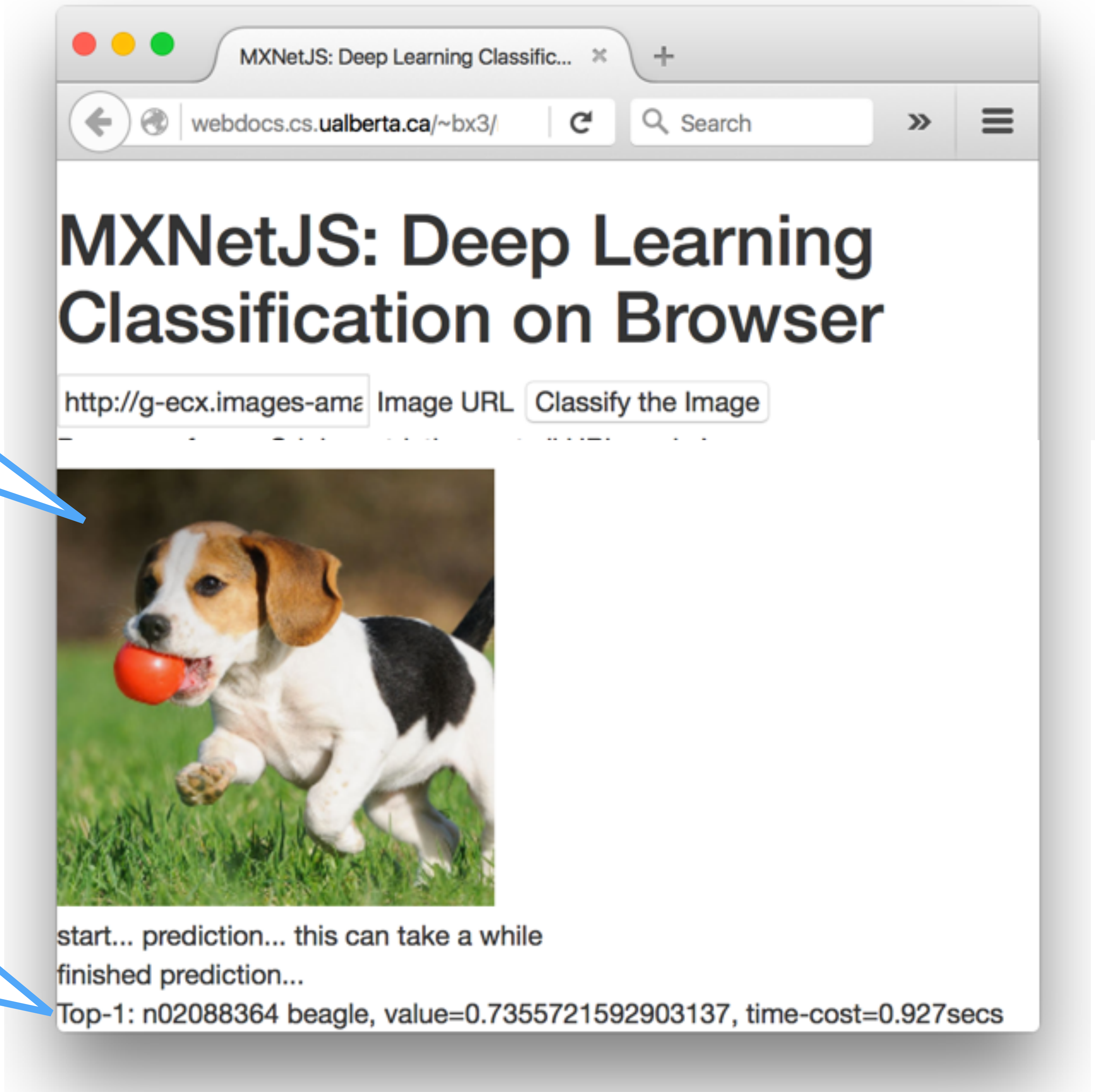
Runs in browser with Javascript

The first image for search “dog” at images.google.com

Outputs “beagle” with prob = 73% within 1 sec

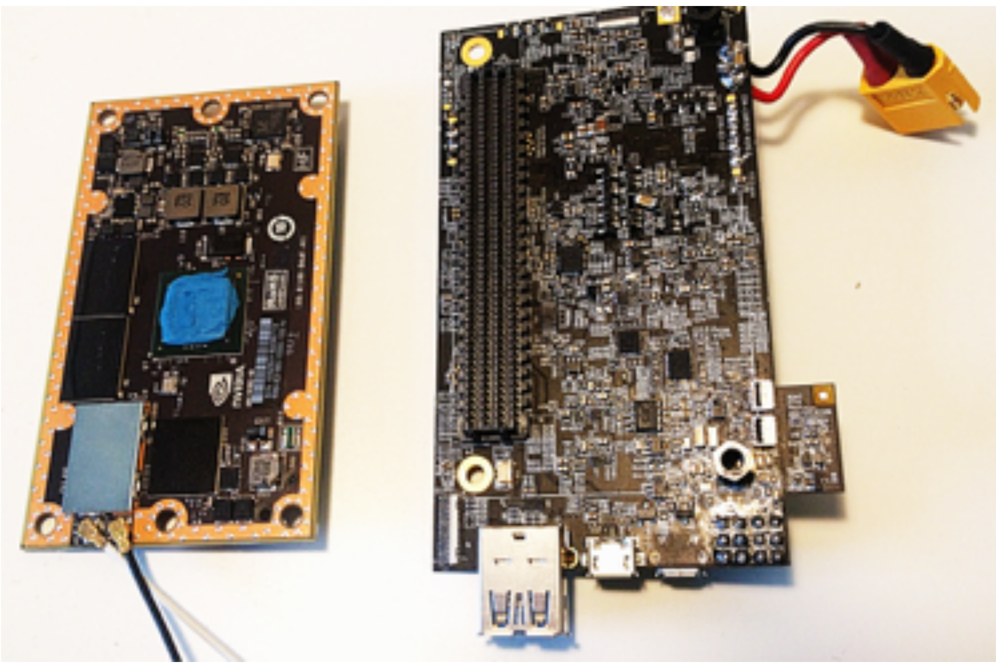


TX1 on Flying Drone

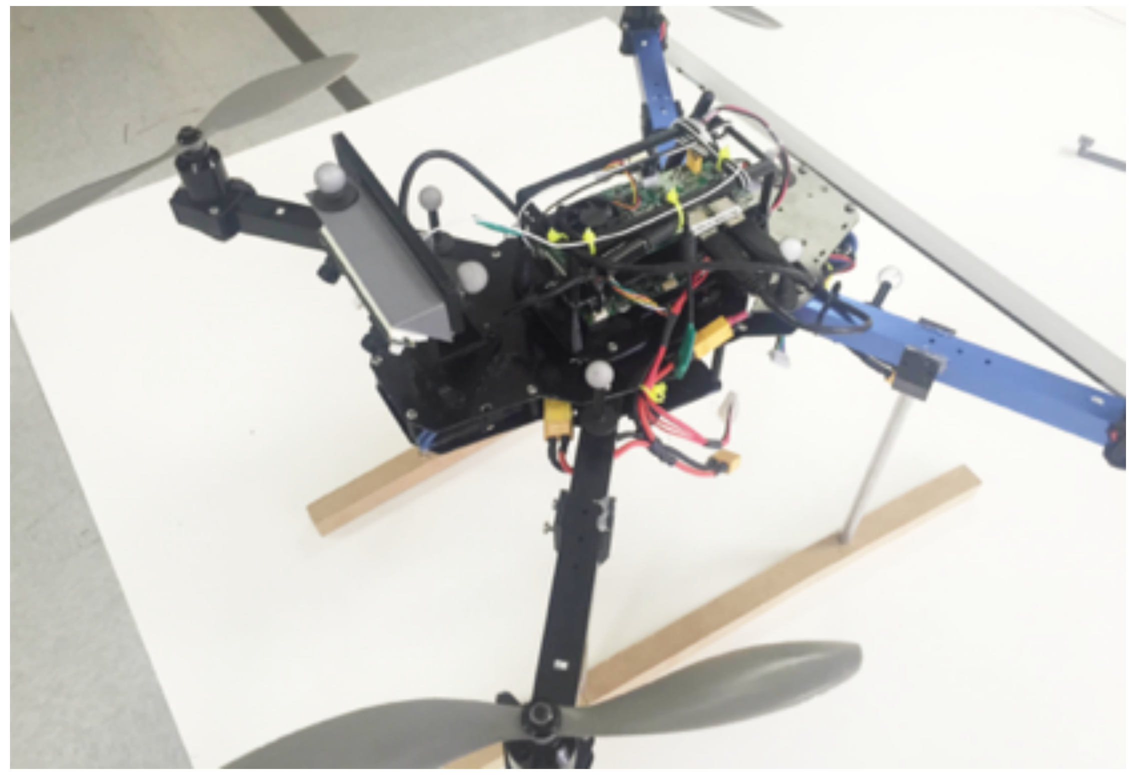
AEVENA

图森 tu Simple

TX1 with customized board



Drone



TX1 on Flying Drone

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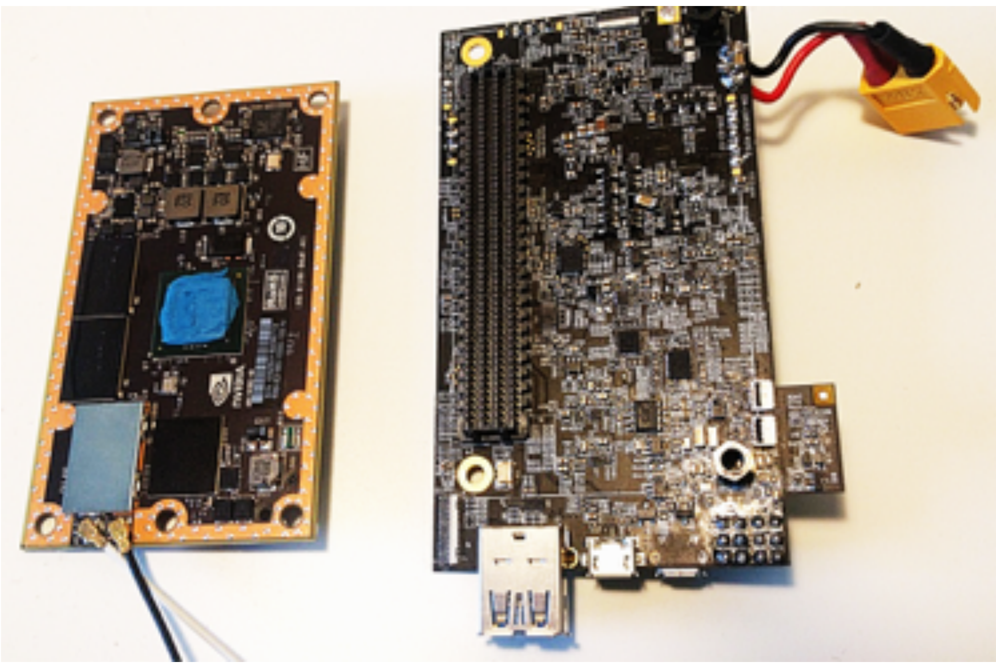
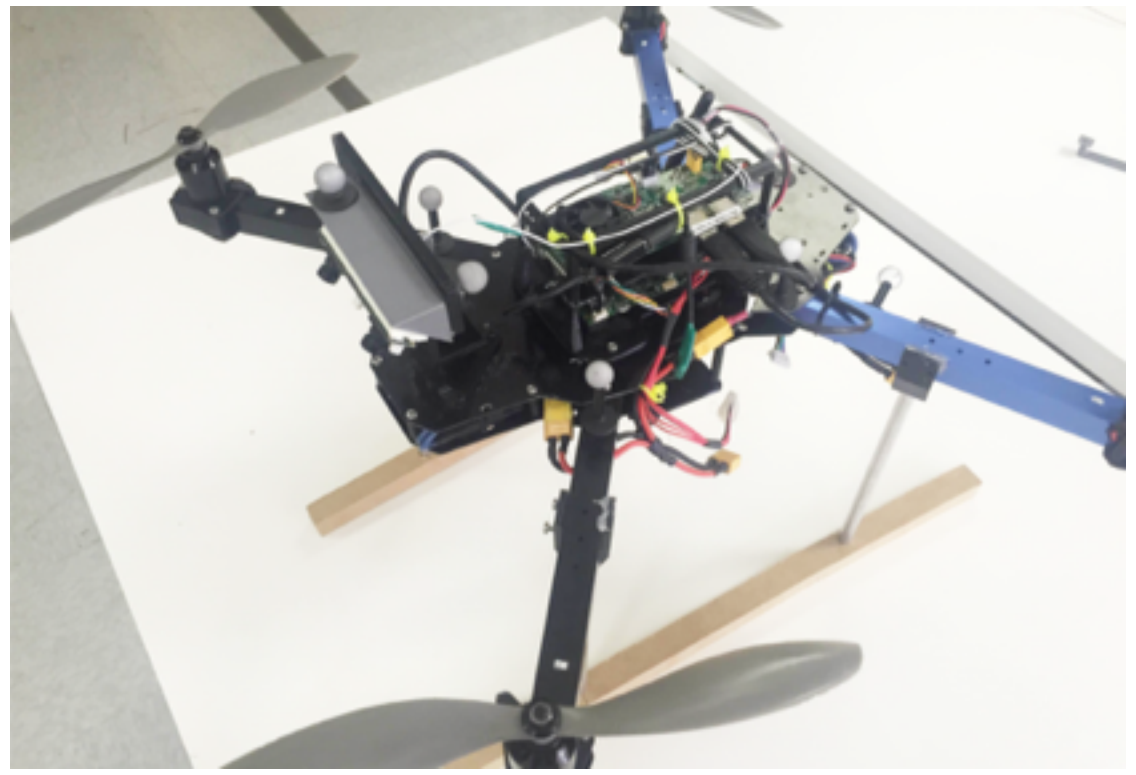
TX1 with customized board

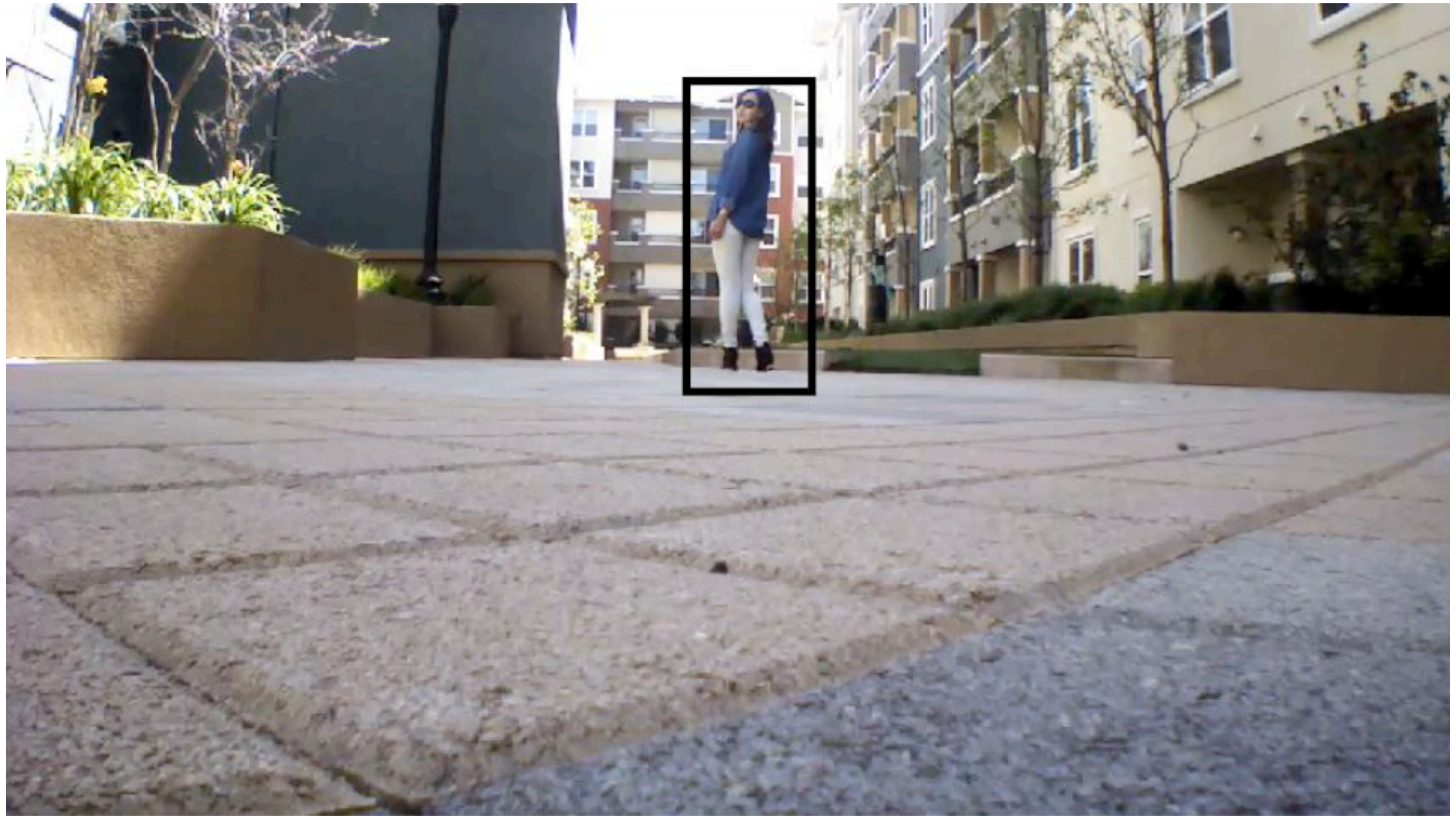


Drone

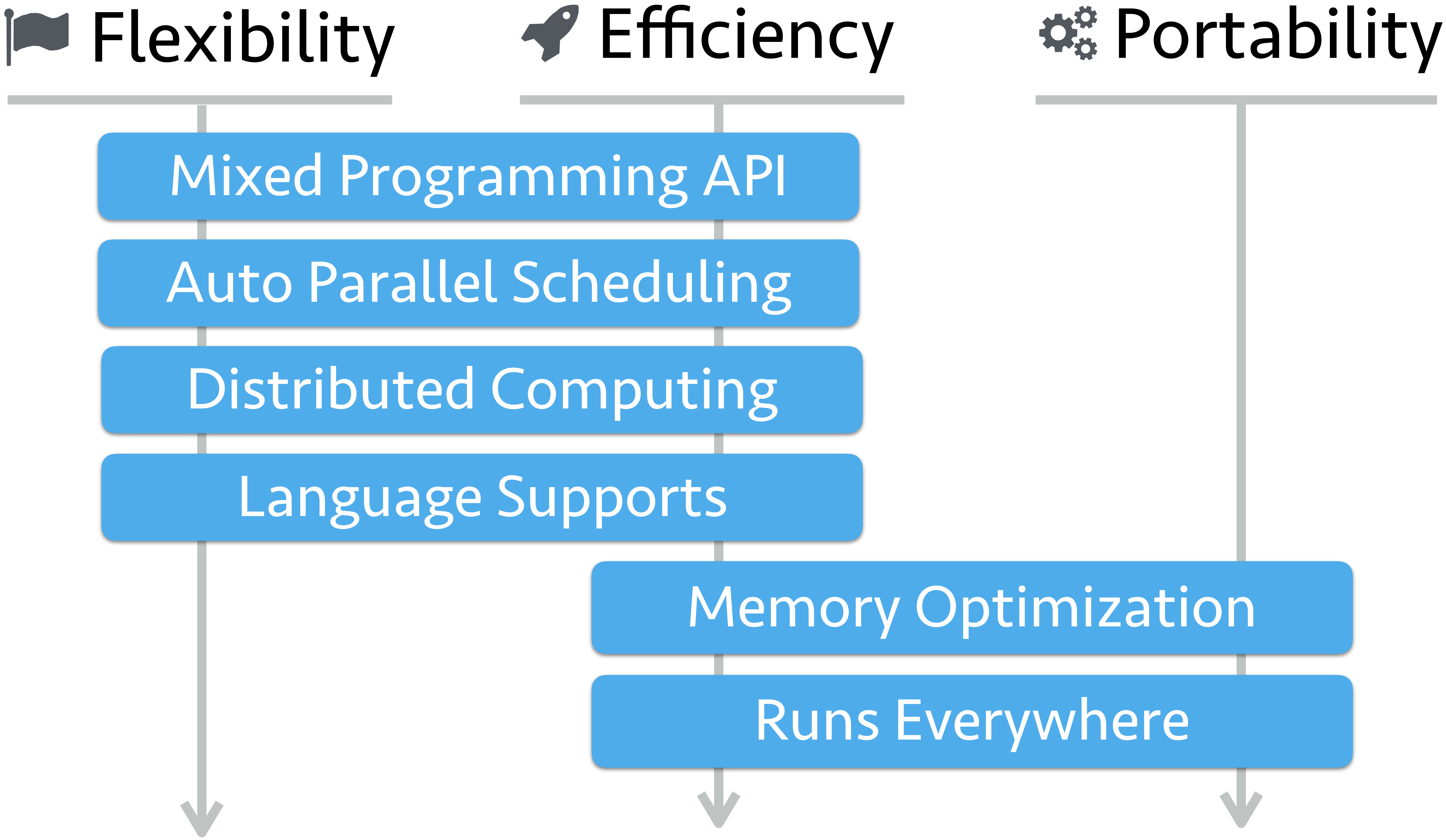


Realtime detection and tracking on TX1

~10 frame/sec with 640x480 resolution



Conclusion


Flexibility
Efficiency
Portability
Mixed Programming API
Auto Parallel Scheduling
Distributed Computing
Language Supports
Memory Optimization
Runs Everywhere

Acknowledgement

MXNet is developed by over 100 collaborators

Major Developers

Bing Xu Dato	**Eric Xie** U Washington	**Chiyuan Zhang** MIT	**Minjie Wang** NYU
Naiyan Wang TuSimple	**Yizhi Liu** MediaV	**Tianjun Xiao** Microsoft	**Yutian Li** Standford
Yuan Tang Uptake	**Qian Kou** Indiana University	**Min Lin** Qihoo360	**Chutao Hong** Microsoft
Tong He Simon Fraser University	**Hu Shiwen** Shanghai		

Advisors

Zheng Zhang NYU Shanghai	**Alex Smola** CMU	**Carlos Guestrin** U Washington

Hardware and software supports

NVIDIA

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