MXNet: Lightweight, Flexible, and Efficient Deep Learning Library

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MXNet is developed by over 100 collaborators

Special thanks to

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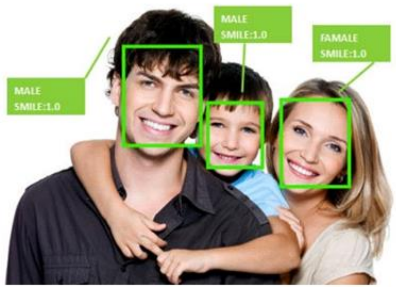
Deep Learning

Image Understanding



Speech Recognition

Natural Language Processing

“Deep Learning” trend in the past 10 years

Packages

TensorFlow

torch

Chainer

dmlc mxnet

theano

Caffe

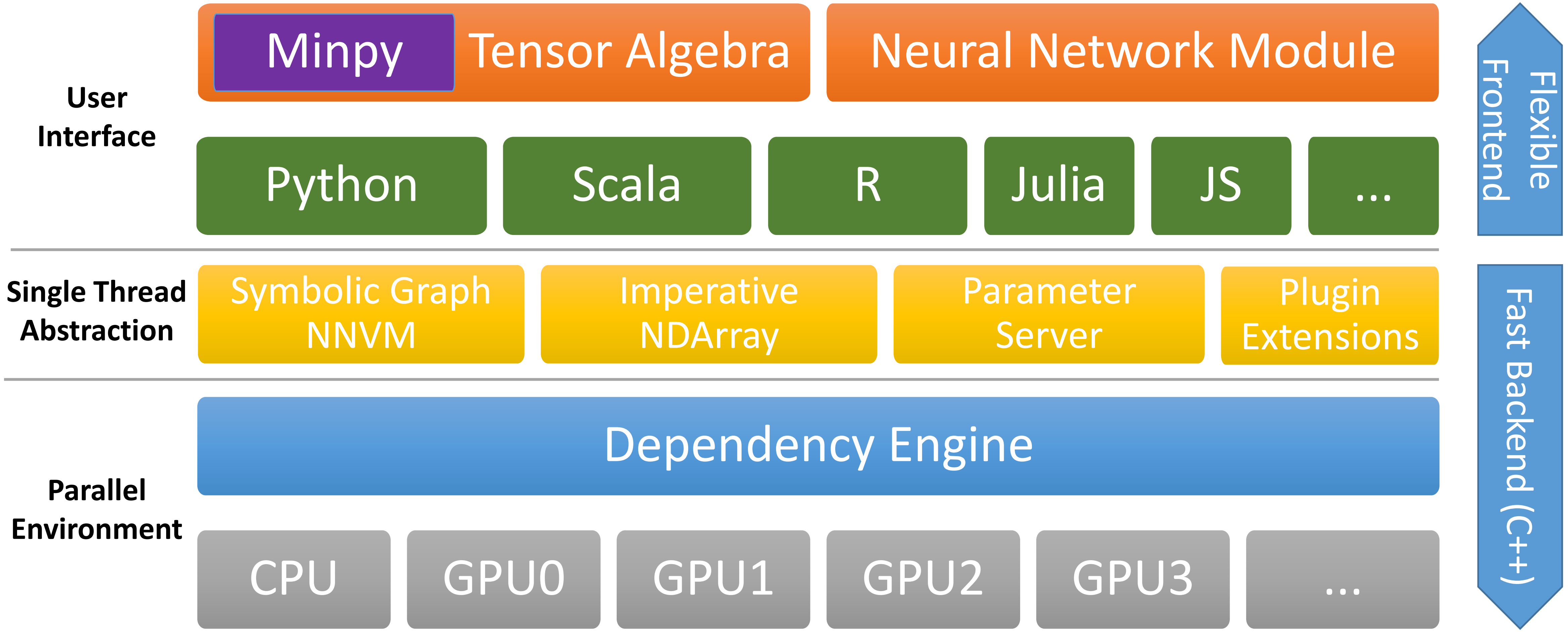
K

Microsoft CNTK

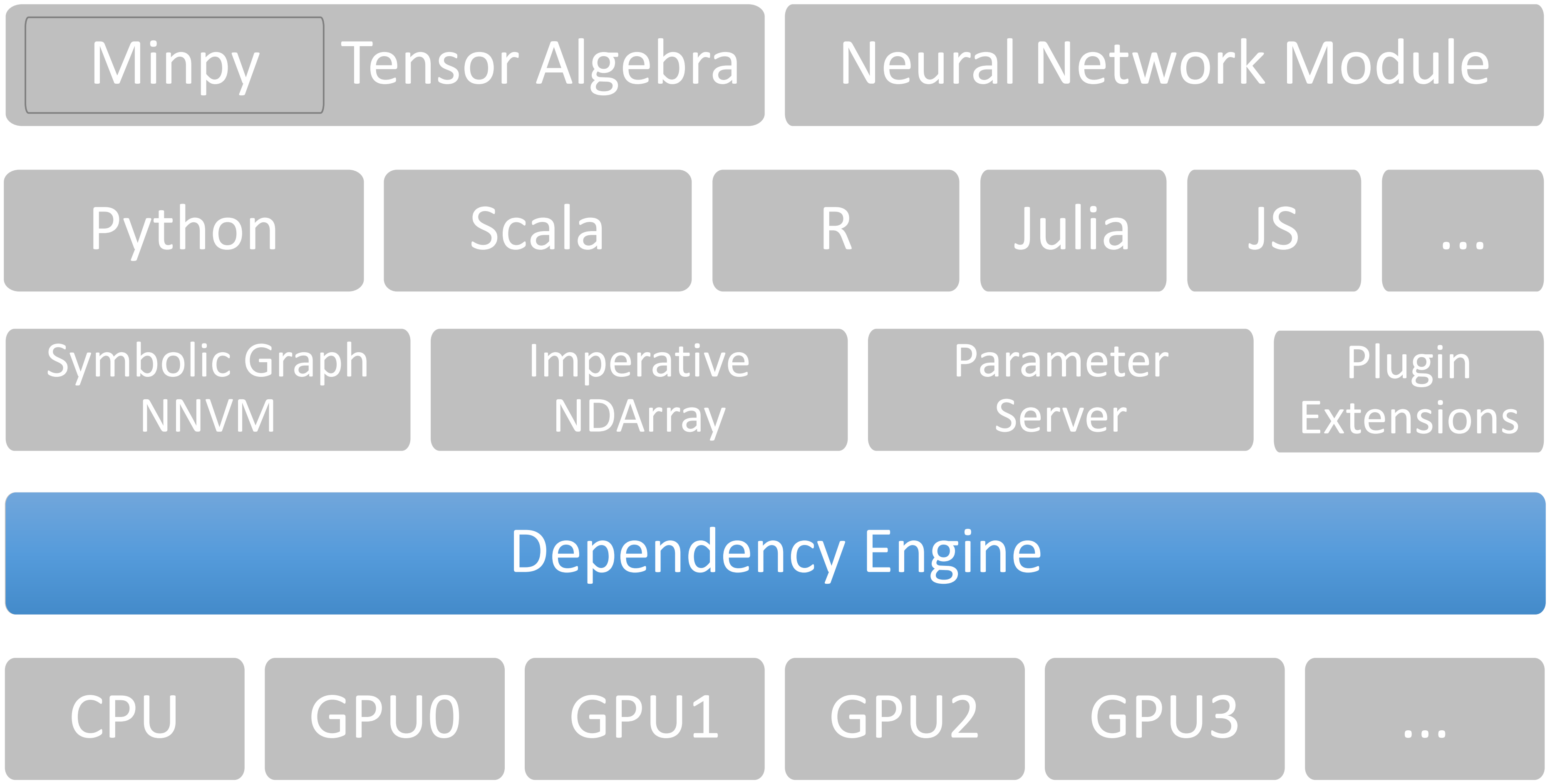
MXNet's Approach

- Lightweight
- User defined flexibility-efficiency trade-off
- Transparent scaling
- Deploy everywhere
- Modular and extendable
- Mixed declarative and imperative programming
- Community driven open source

The MXNet Stack

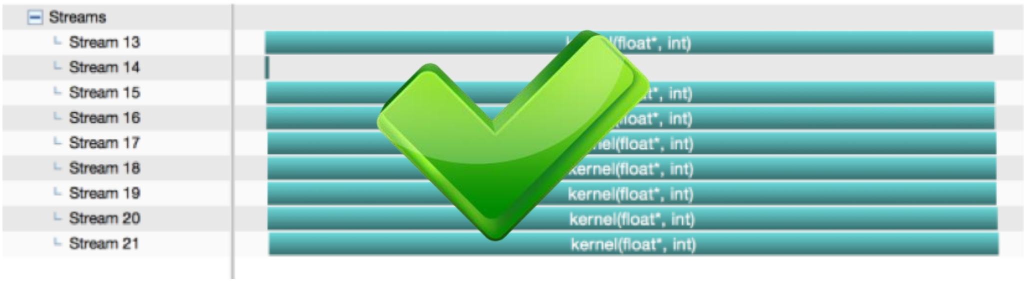


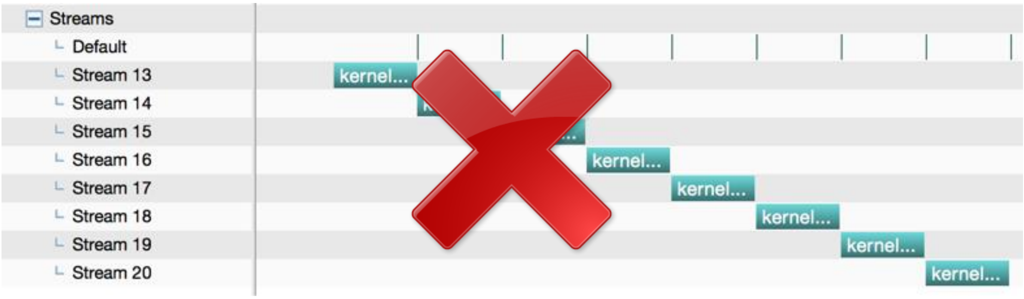
Dependency Scheduling Engine



Need for Parallelism

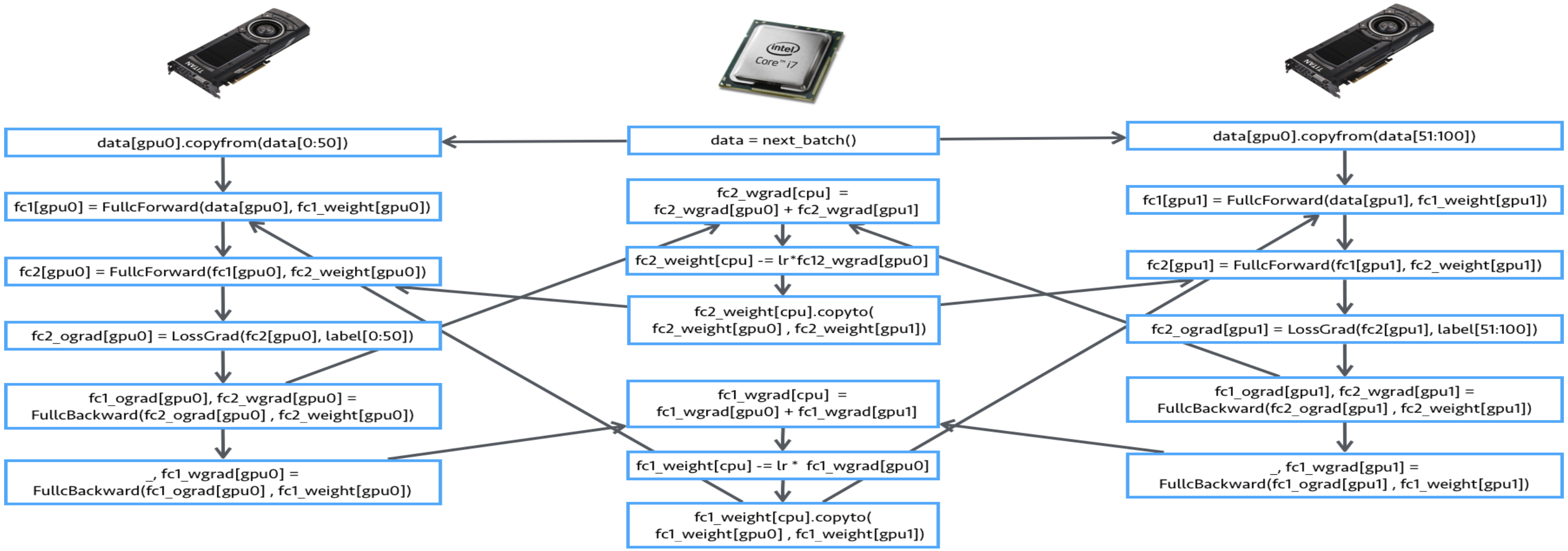
- Speed is critical to deep learning
- Parallelism leads to higher performance
  - Parallelization across multiple GPUs
  - Parallel execution of small kernels
  - Overlapping memory transfer and computation
  - …





Parallel Programs are Painful to Write…

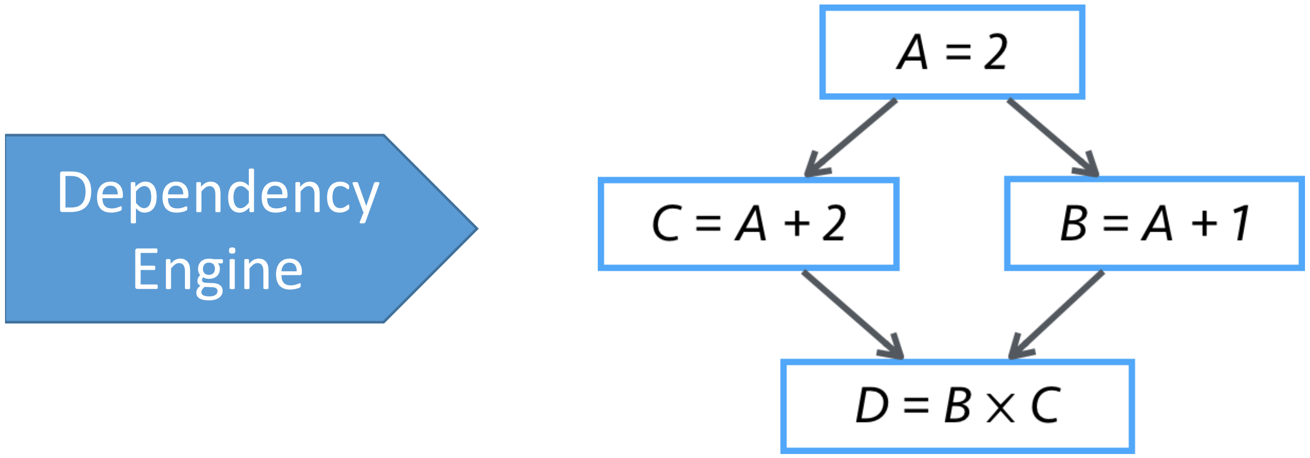
- … because of dependencies



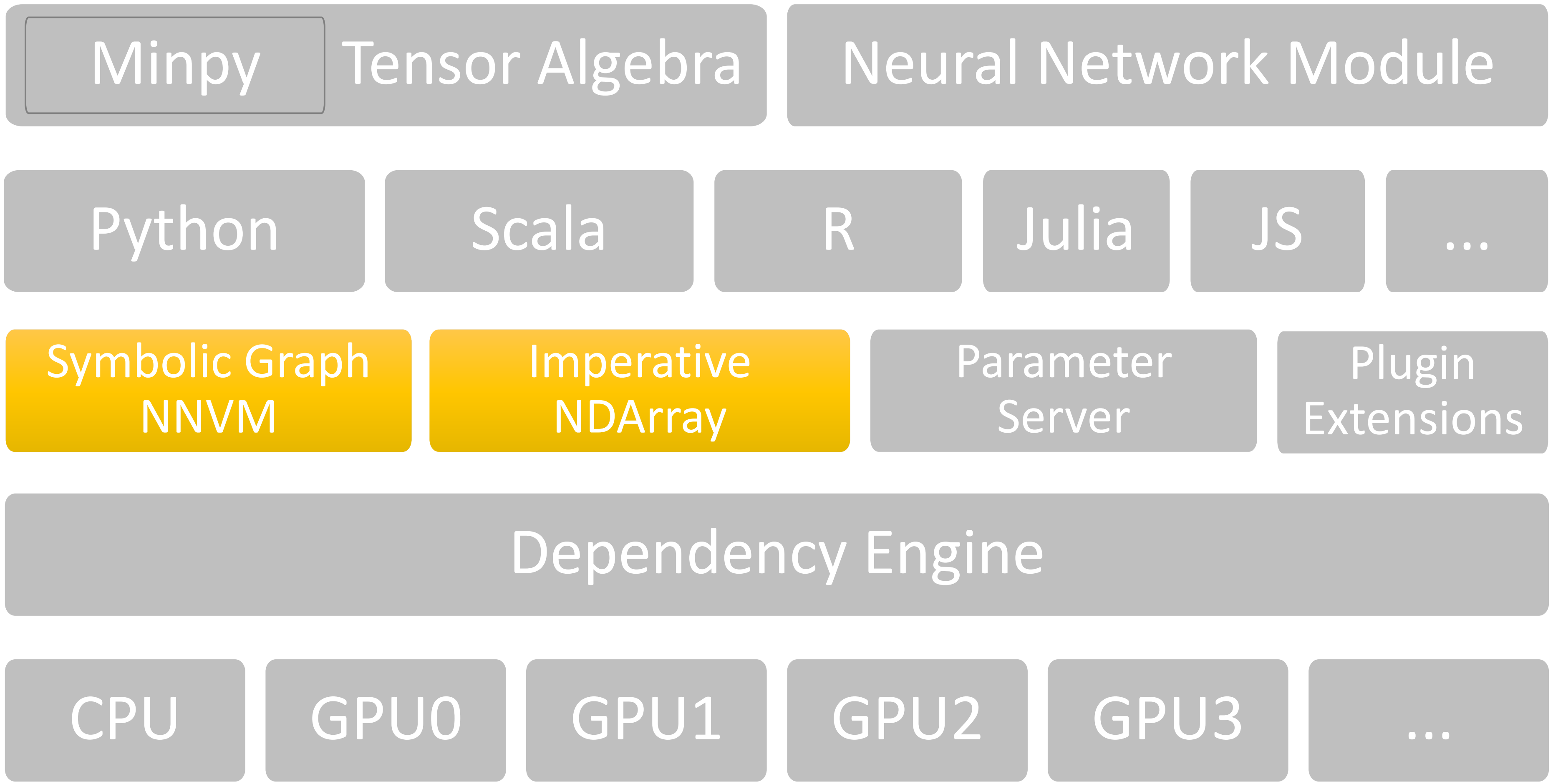
Solution: Auto Parallelization with Dependency Engine

- Single thread abstraction of parallel environment

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

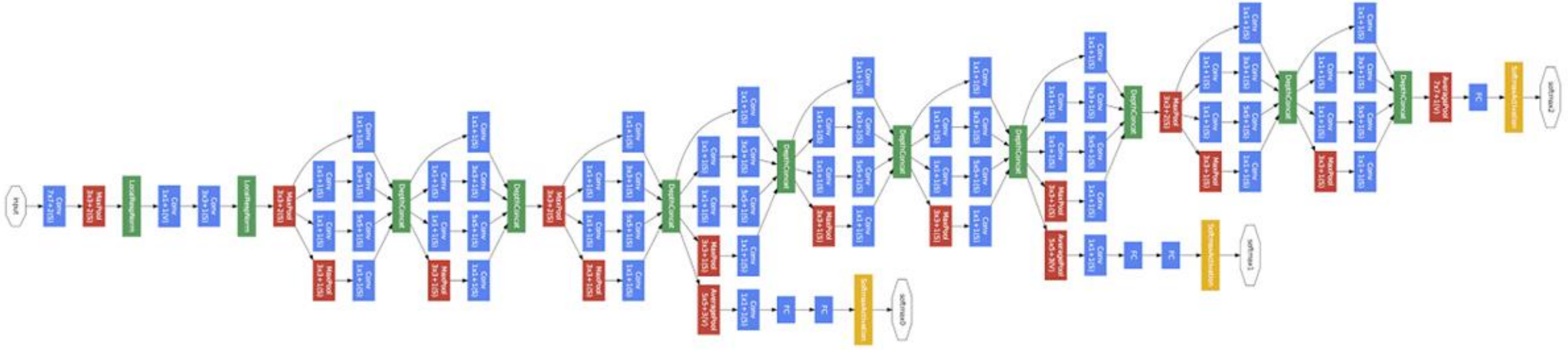


Symbolic vs. Imperative Deep Learning



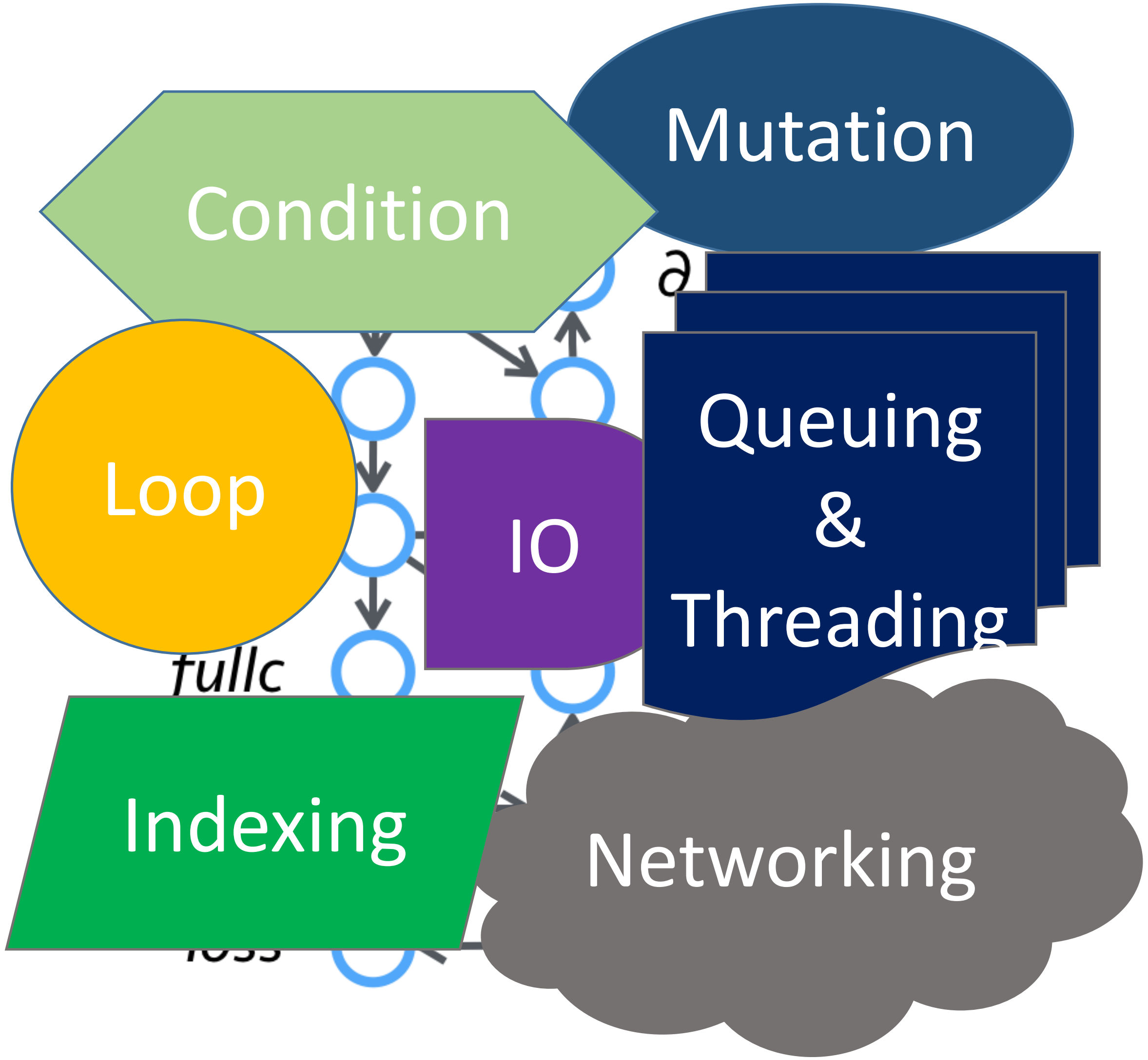
Neural Networks as Symbolic Graph

- Most packages represent networks as graphs
  - MXNet, Caffe, Theano, Tensorflow, CNTK, …
- Easy to store, port, and optimize
  - Parallelization, buffer sharing, operator fusion, serialize and deploy, …



Deep Learning is More Than DAG

- All is good …
  - … until you start adding too many things to it …



You just reinvented programming language

...

and lost most advantages of using graph

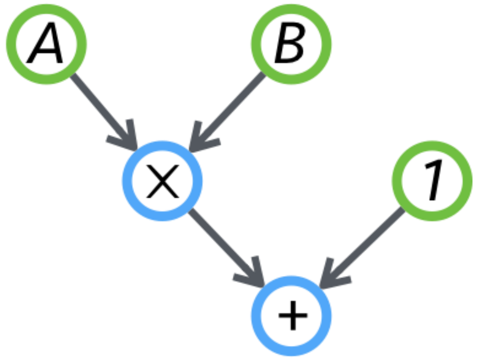
Neural Networks as Imperative Program

- DL, or ML in general, is largely tensor algebra.
  - Torch, Chainer, Matlab, R, Numpy, …
- Imperative programs are flexible but hard to optimize:

```
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)
```



Neural Networks as Imperative Program

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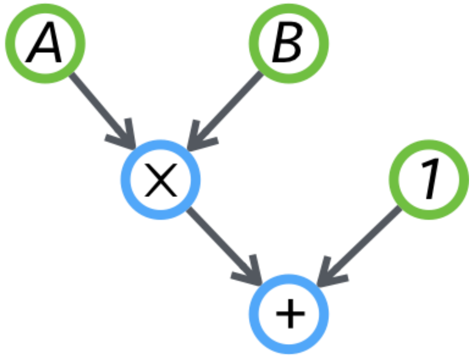
```
import numpy as np
a = np.ones(10)
b = np.ones(10) * 2
c = b * a
d = c + 1
```

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

MXNet’s Approach: Mixed Programming

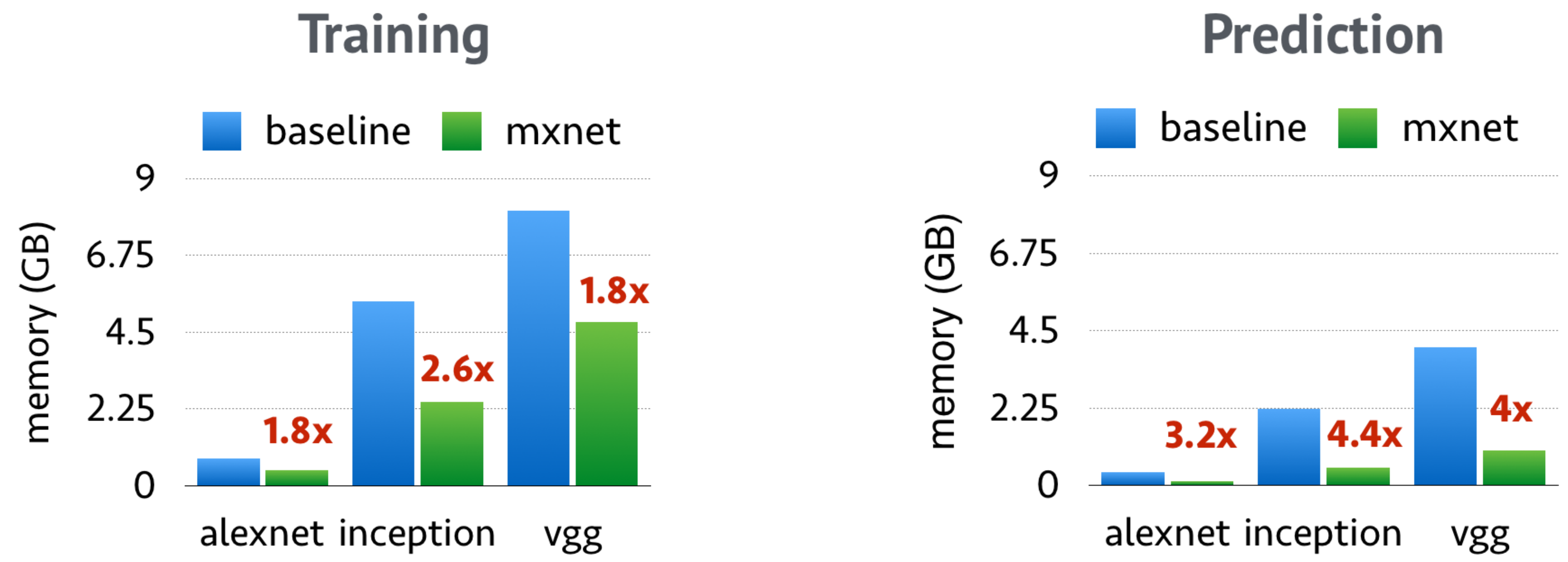
- Mix symbolic and imperative operations to get benefit of both.
- Symbolic graph: heavy, standard operations.
  - >90% of runtime, <10% of coding time.
- Imperative program: light, project specific operations.
  - <10% of runtime, >90% of coding time.
- Dependency Engine allows seamless combination of two parts.
- Only optimize the bottleneck!

MXNet’s Approach: Static Graph

- In MXNet, graphs are simple and static:
  - Simple DAG without fancy logic
  - Fixed topology and tensor shapes
- Static graphs are:
  - Faster to build: multiple graphs instead of loop and condition.
  - Easier to optimize: Static memory planning, asynchronous execution, …
- Flexibility compensated by imperative operations.

Smallest GPU Memory Footprint

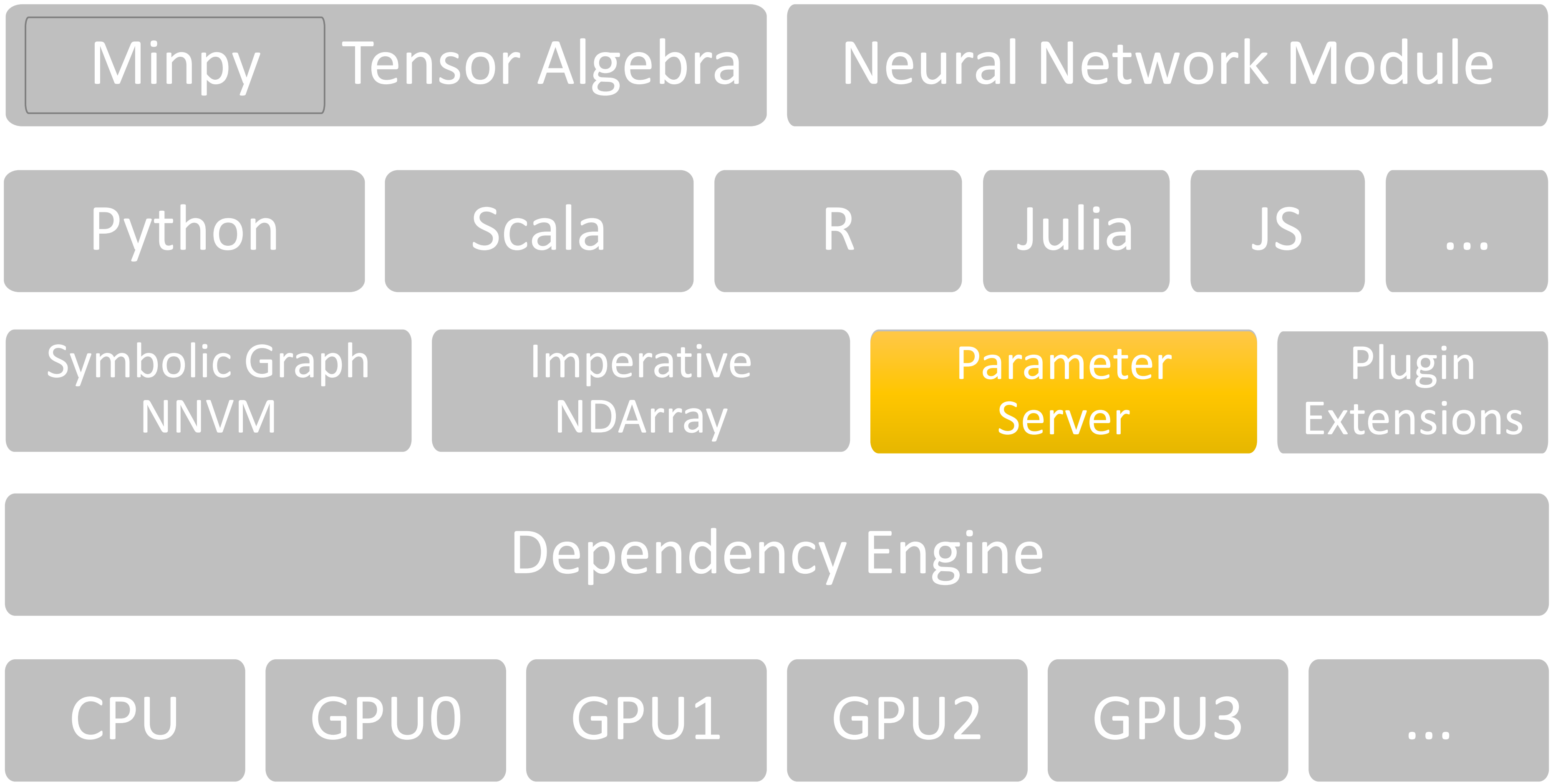
- Static graph enables aggressive memory sharing.



Trade Speed for Memory

- MXNet Mirror:
  - Discard result of small Ops on forward pass (ReLU, BN, etc).
  - Re-compute on backward pass.
  - 30%-50% memory saving at 90% speed.
- MXNet Memmonger:
  - Only keep result of $\sqrt{N}$ (anchor layers) out of N layers on forward pass.
  - Re-compute $\sqrt{N}$ layers between two anchor layers on backward pass.
  - Train $\mathrm{O}(\sqrt{N})$ times larger model at 75% speed.

Parallel & Distributed Training

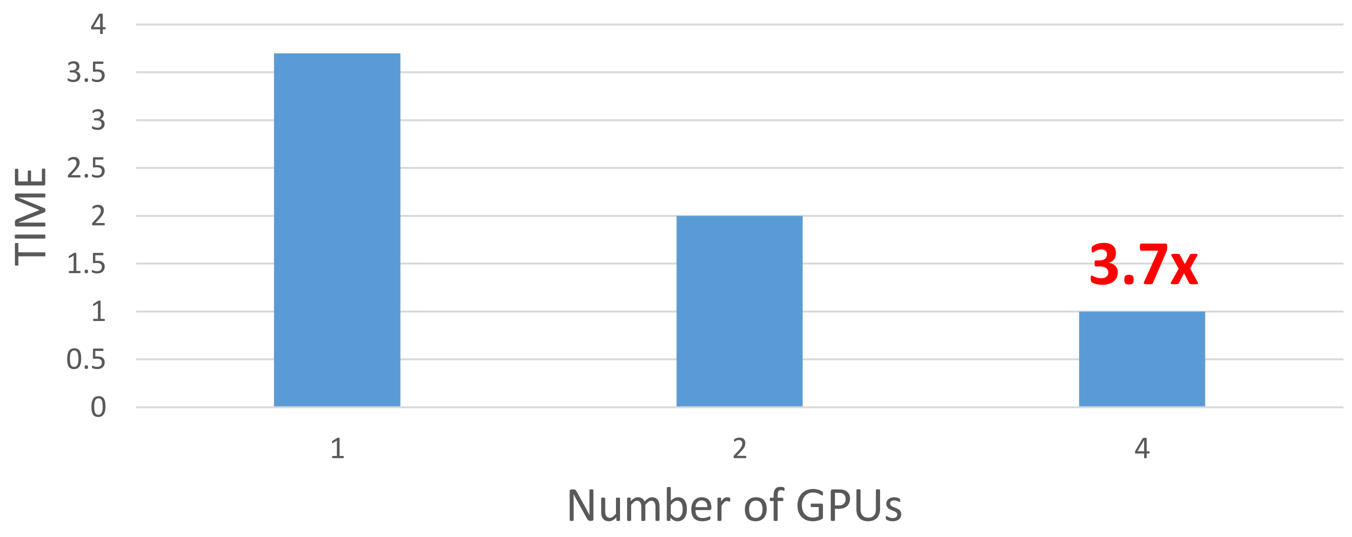


Drop-in Parallel Training

- Scaling to Multi-GPU machine as easy as one line change:

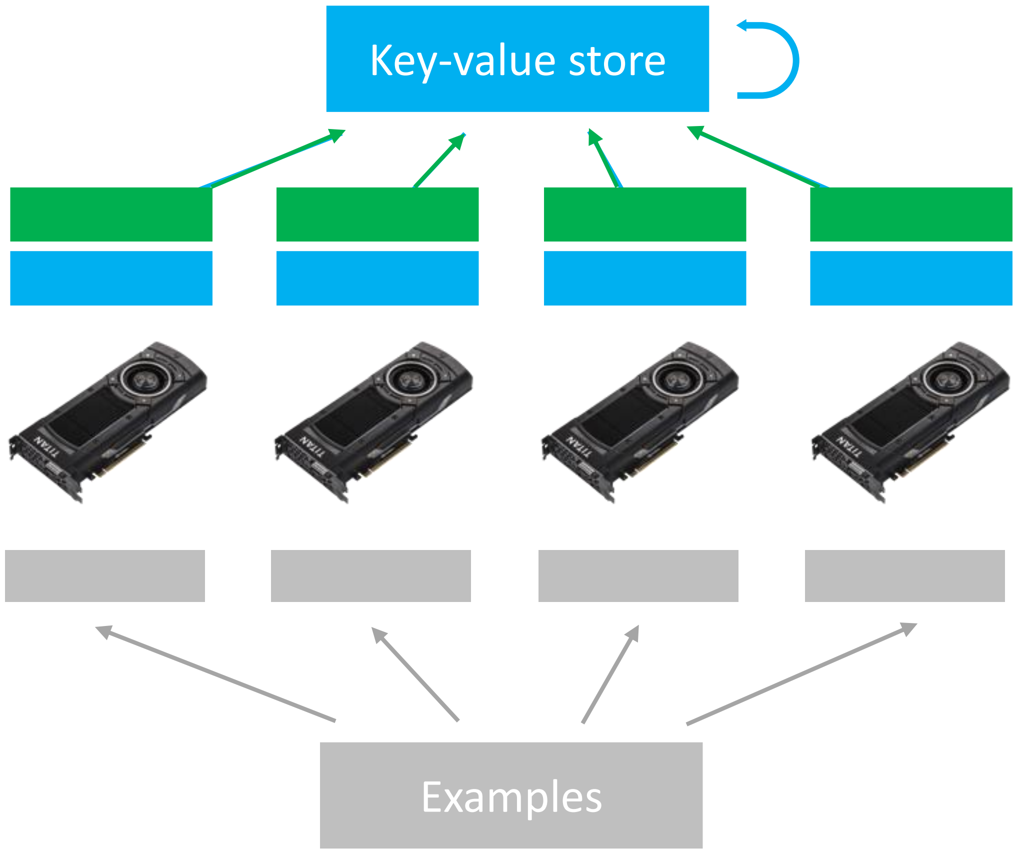
```
model = mx.mod.Module(net, ctx=mx.gpu(0))
-> model = mx.mod.Module(net, ctx=[mx.gpu(0), mx.gpu(1)])
```

- Near linear speedup on a single machine:



Parallel Training: Under the Hood

- Read a data partition
- Pull the weight
- Compute the gradient
- Push the gradient
- Update the weight



Distributed Training

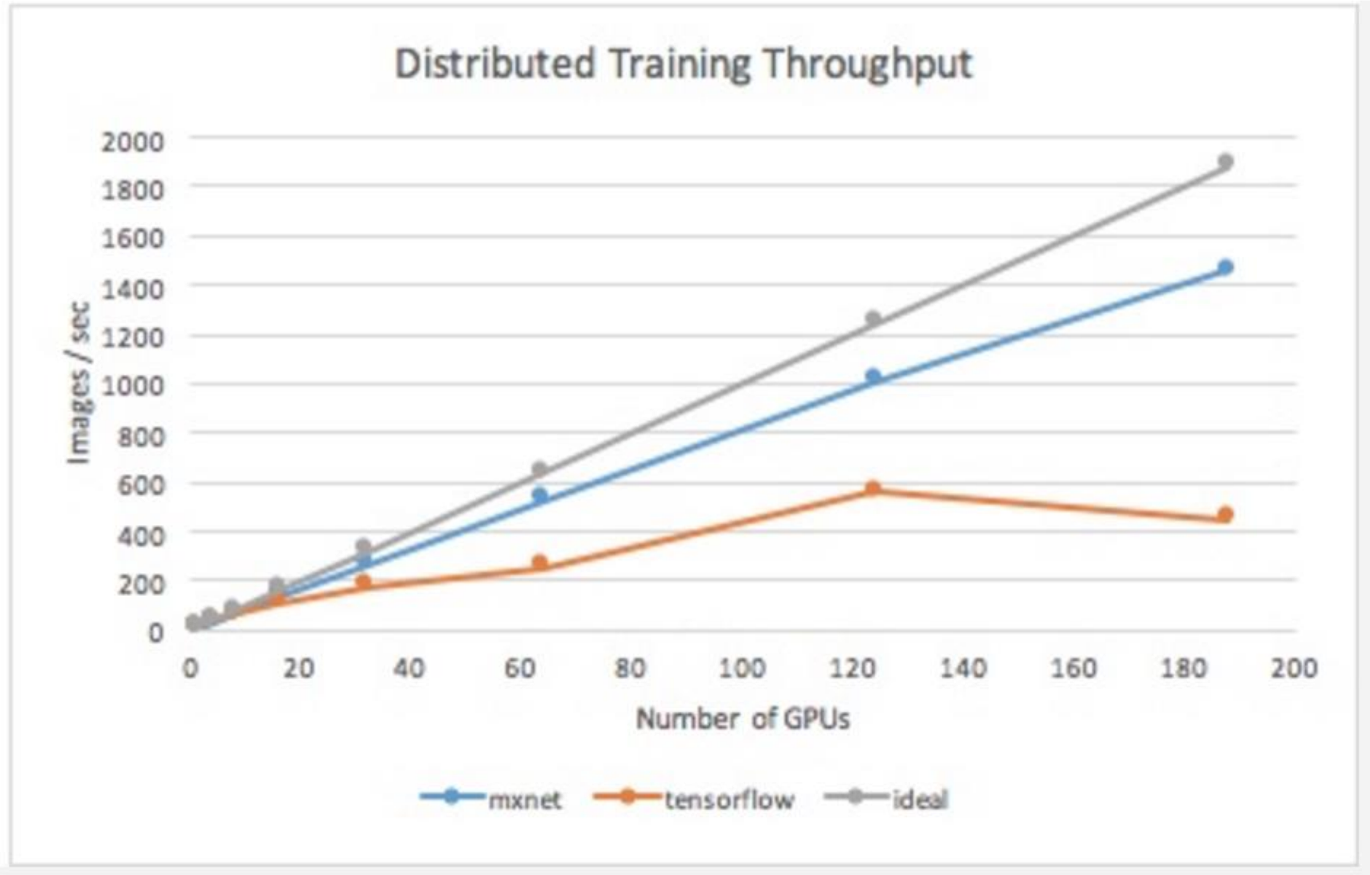
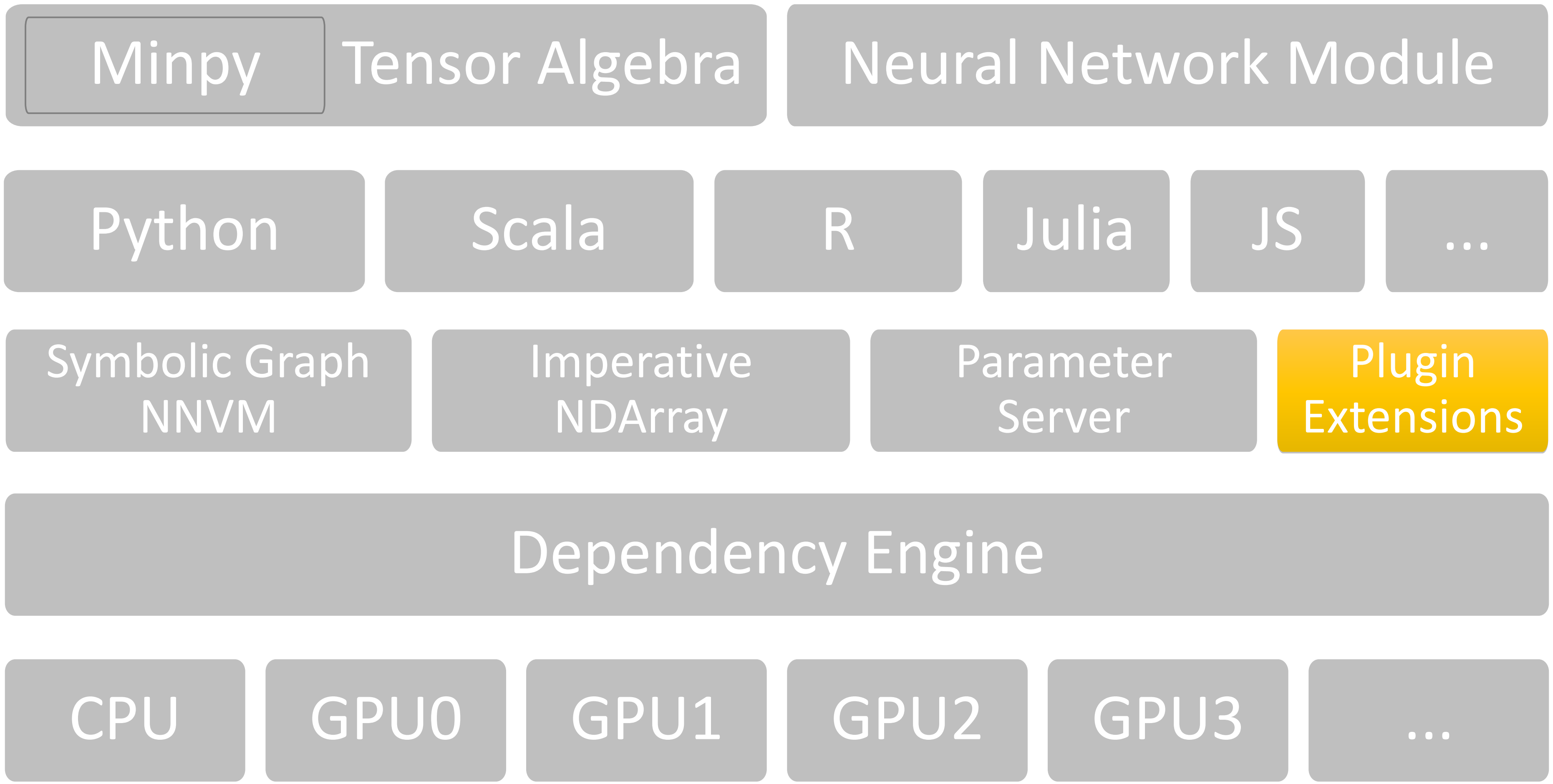


Figure by Carlos Guestrin @Turi

- Scale to multi-machine with the same key-value store interface.
- 2x faster than Tensorflow on >10 4GPU machines
- Latest Update: 74x acceleration on 10 machines with 8GPUs in each machine.

Parallel & Distributed Training



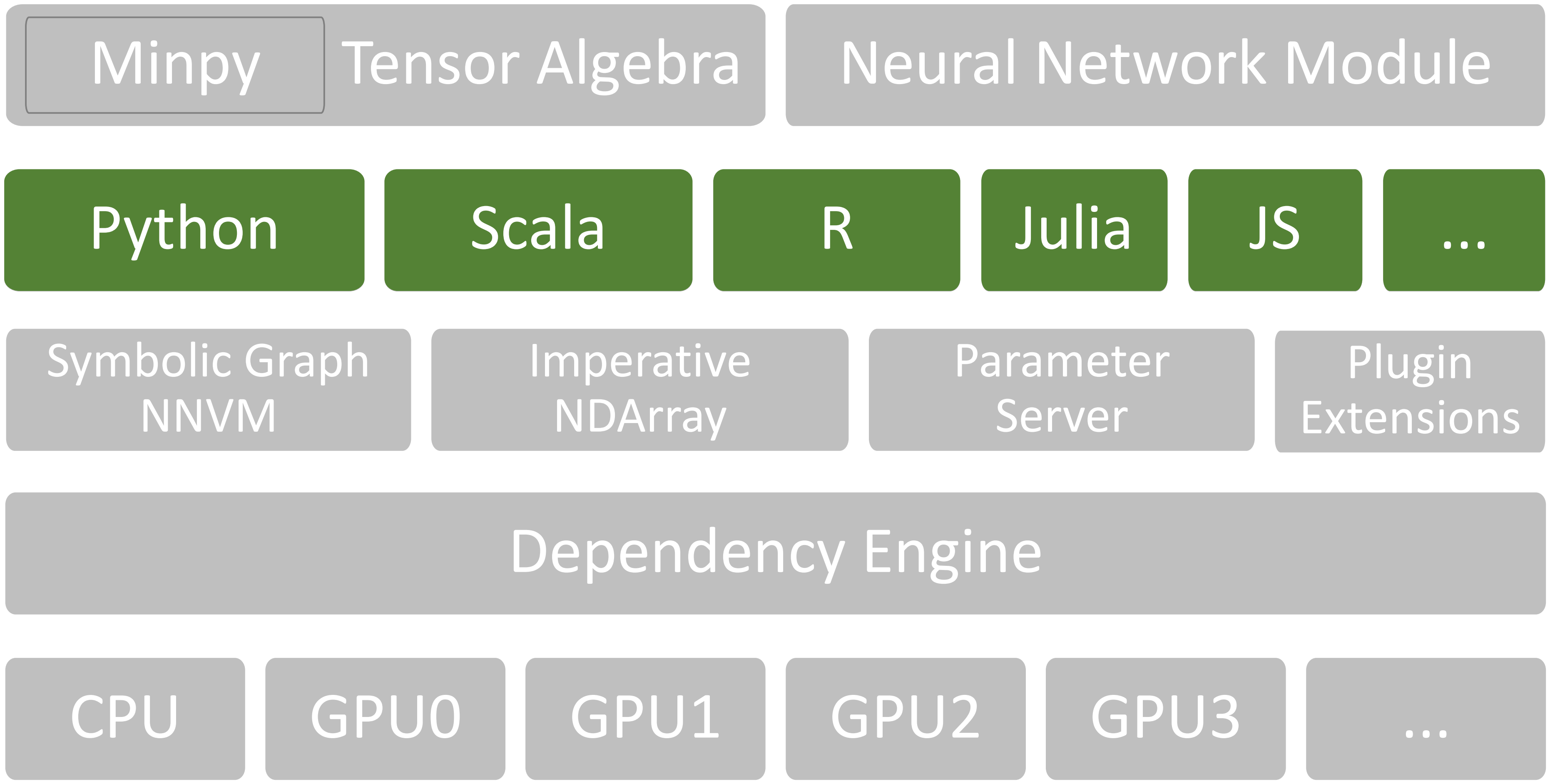
Plugin Extensions

- TorchModule:
  - Use Torch NN layers and tensor functions in MXNet graph.
    fc1 = mx.sym.TorchModule(lua_string='nn.Linear(784, 128)', …)
- CaffeOp:
  - Use Caffe layers in MXNet graph.
    fc1 = mx.symbol.CaffeOp(prototxt="layer{type:\"InnerProduct\”
    inner_product_param{num_output: 128} }”, …)
- WrapCTC:
  - Use Baidu’s CTC module for sequence learning in MXNet.
- OpenCV:
  - Multi-threaded OpenCV interface that by pass GIL for fast image IO.

Mainstream Applications in Vision/NLP/Speech

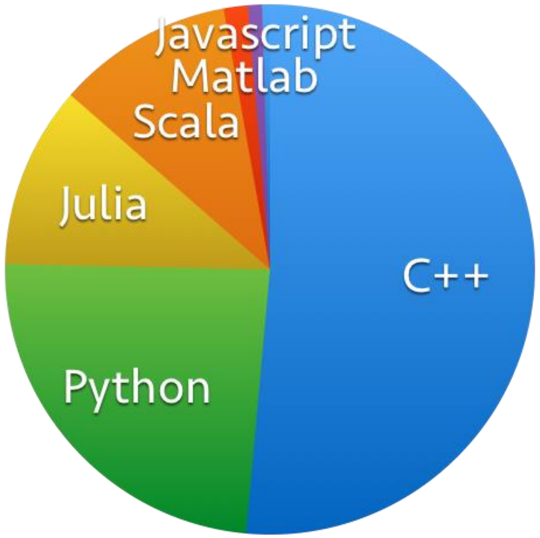
- Image Classification
  - Inception/ResNet
- Object Detection
  - Faster RCNN
- Image Segmentation
  - FCN/Deeplab
- OCR
  - Warp-CTC
- Char LSTM/Char CNN/Speech Acoustic Modeling/Neural Art…

Runs Everywhere



Code with Any Language

Lines of code



Train in the Cloud

Load 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

Amalgamation

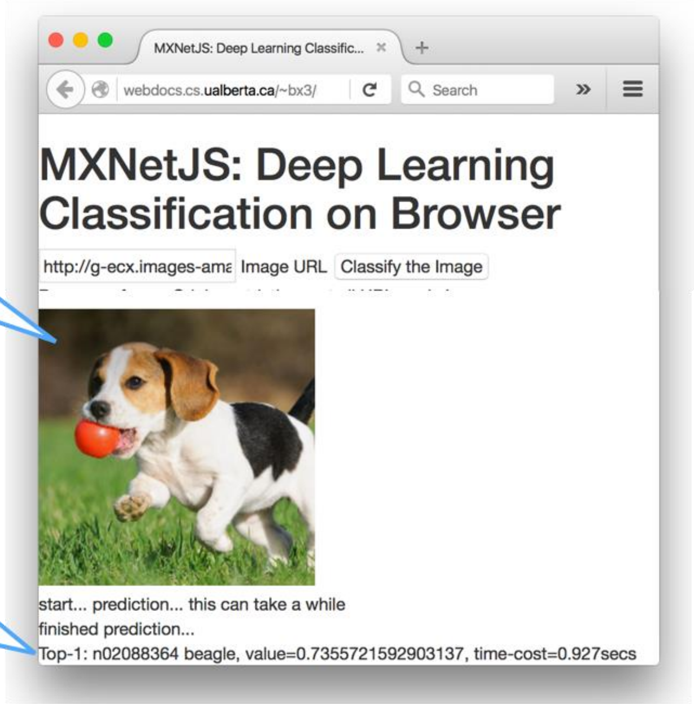
- Fit the core library with all dependencies into a single C++ source file
- Easy to compile on …

BlindTool by Joseph Paul Cohen, demo on Nexus 4

Runs in browser with Javascript

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

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



Thanks