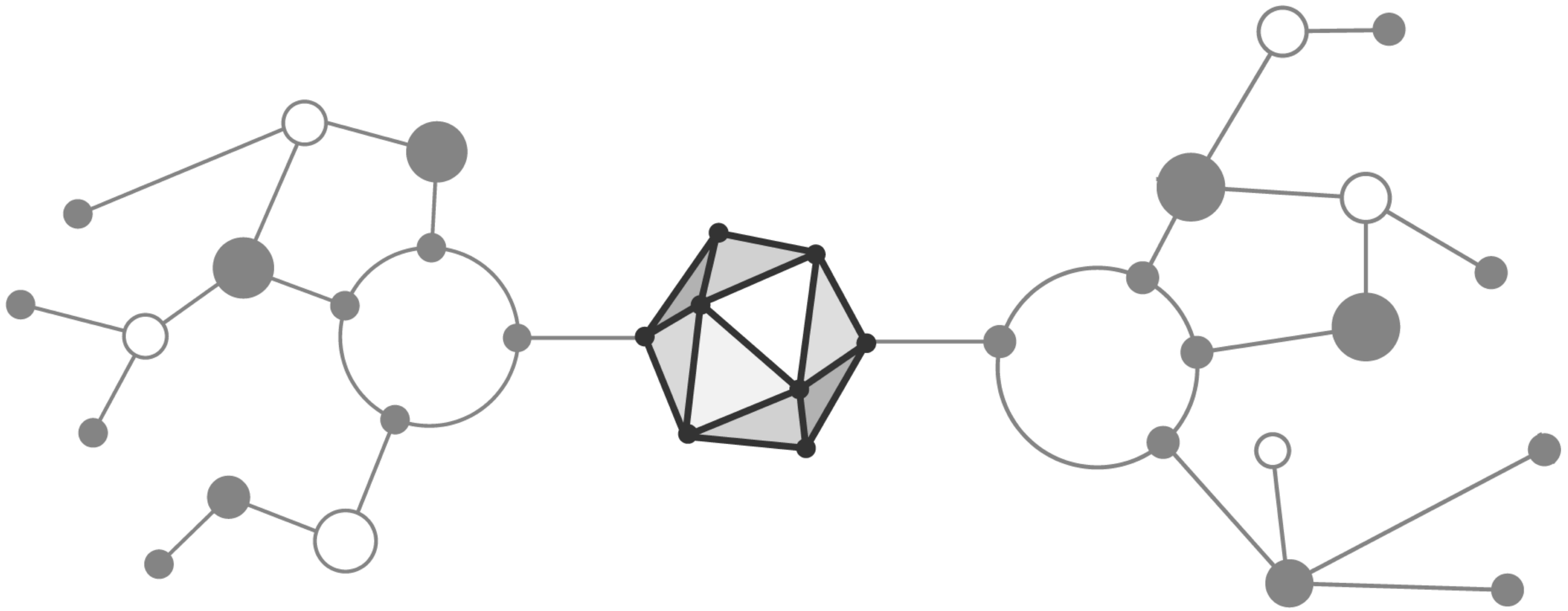
facebook

ONNX



Sarah Bird, Dmytro Dzhulgakov

Facebook

Deep Learning Frameworks

PYTORCH

Tensors and Dynamic neural networks in Python with strong GPU acceleration

Flexible Development

- Research-oriented imperative model
- Python flow-control constructs
- Dynamic graph support with autograd

http://pytorch.org

Released Jan 18th

500,000+ downloads

2700+ community repos

17,200+ user posts

351 contributors

Caffe2

A New Lightweight, Modular, and Scalable Deep Learning Framework

RUN ANYWHERE, FAST

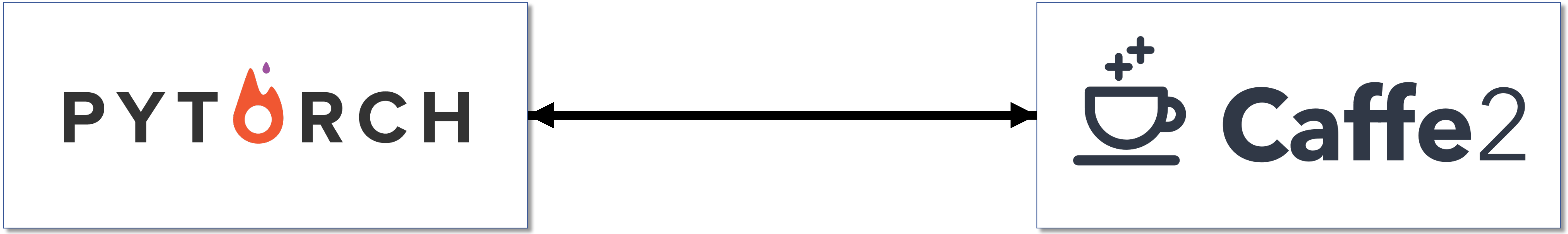
Your favorite deep learning technology, now from zero to scale, cloud to mobile.

Train ImageNet in 1 hour

Production Powerhouse

- Scalable from small devices to large GPUs in DC
- Strong distributed training support
- Highly optimized mobile device support
- Based on ahead-of-time static graph – no interpreter needed in prod

Research to Production



Reimplementation
takes weeks or months

Merge Frameworks?

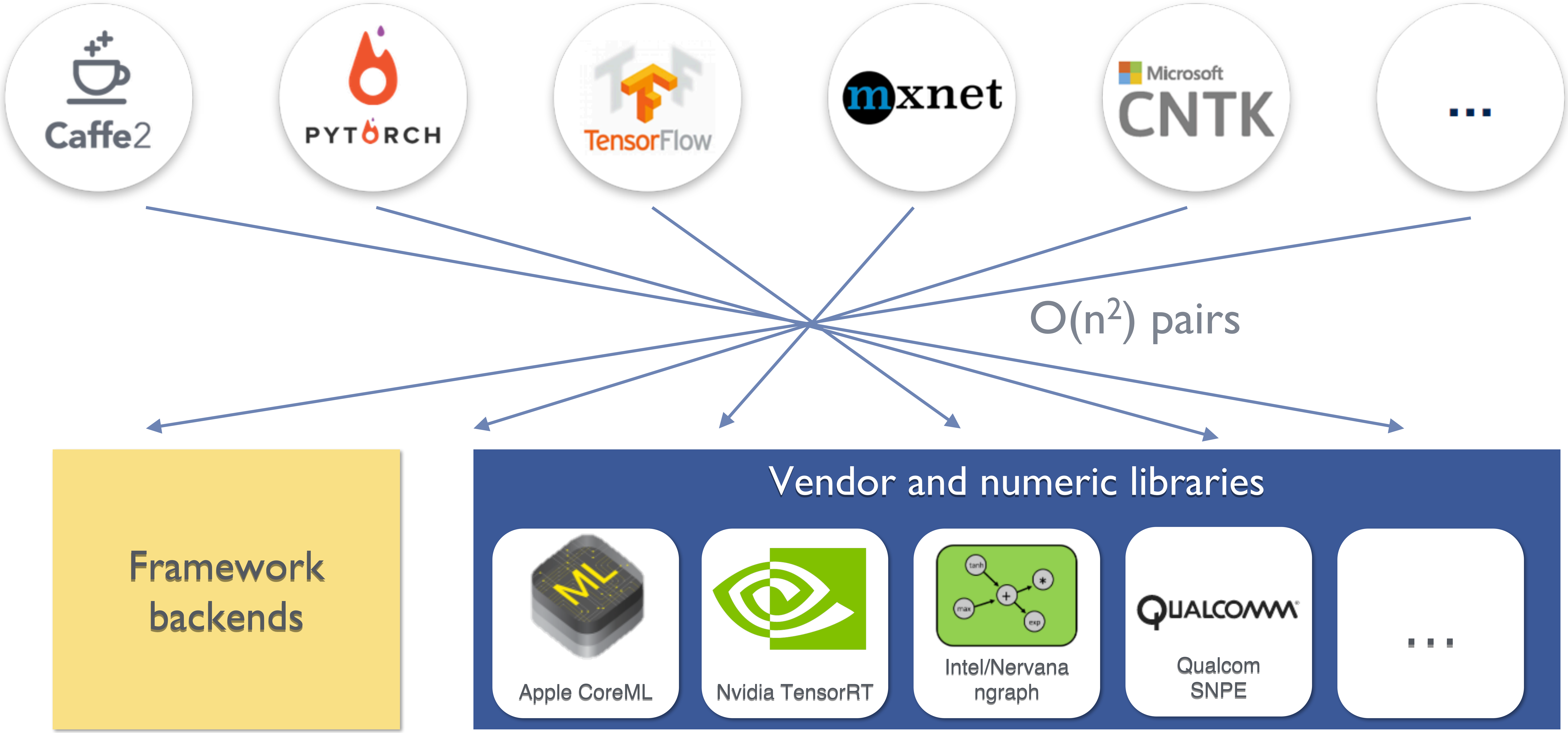
PYTORCH

Caffe2

- Model transfer is important, but less common
- Difficult to optimize the tools for all cases
- Separate but interoperable tools is more efficient

Shared Model Format

Deep Learning Frameworks Zoo



Open Neural Network Exchange

Caffe2

PYTORCH

TensorFlow

mxnet

Microsoft CNTK

...

ONNX

Shared model and operator representation

From $O(n^2)$ to $O(n)$ pairs

Framework backends

Vendor and numeric libraries

Apple CoreML

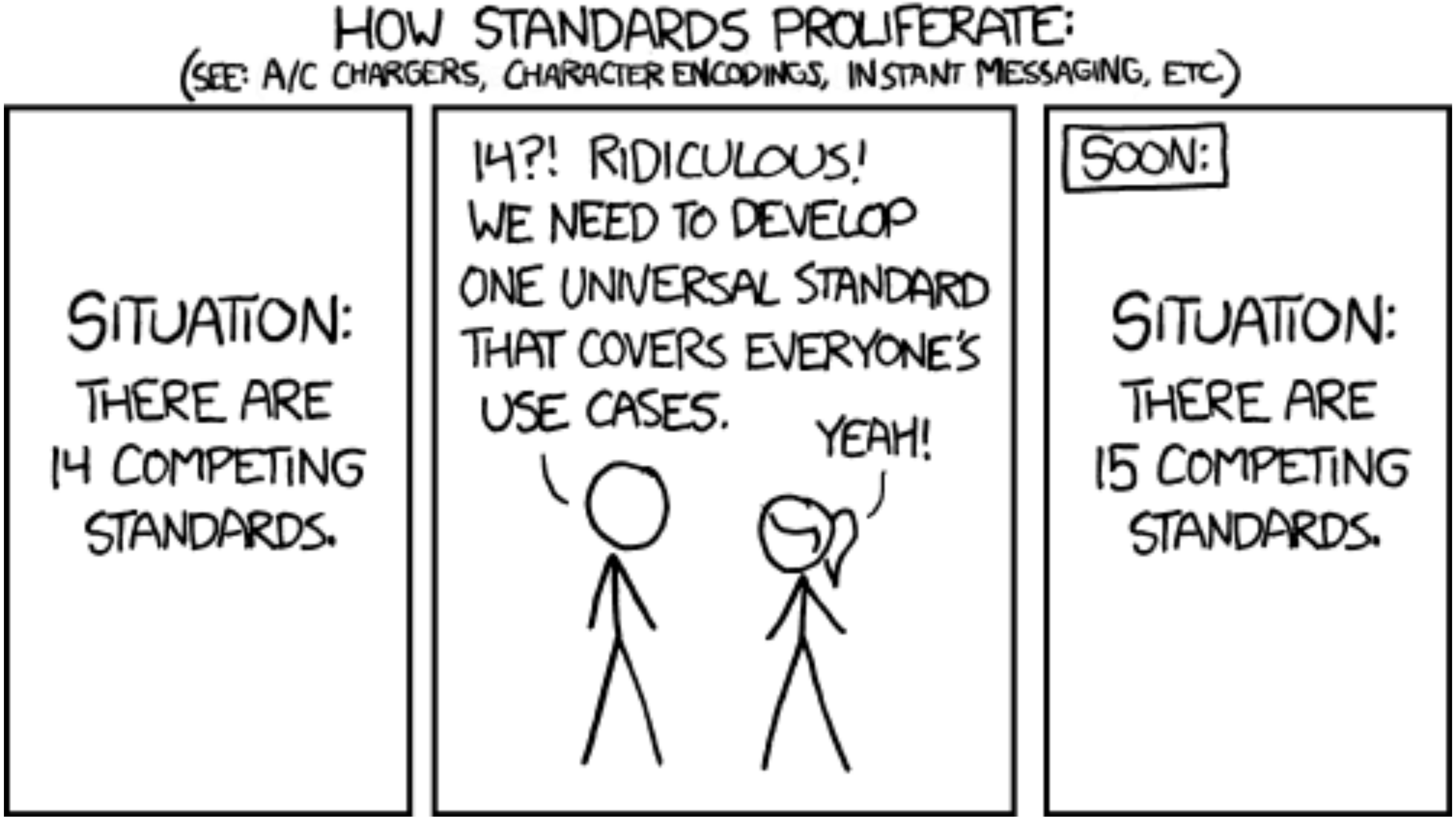
Nvidia TensorRT

Intel/Nervana ngraph

Qualcom SNPE

...

Standard?


HOW STANDARDS PROLIFERATE:
(SEE: A/C CHARGERS, CHARACTER ENCODINGS, INSTANT MESSAGING, ETC)
SITUATION:
THERE ARE 14 COMPETING STANDARDS.
14?! RIDICULOUS! WE NEED TO DEVELOP ONE UNIVERSAL STANDARD THAT COVERS EVERYONE'S USE CASES.
YEAH!
SOON:
SITUATION:
THERE ARE 15 COMPETING STANDARDS.

Open community

- Framework agnostic
- GitHub from the beginning
- Close partnerships and OSS contributions

aws Facebook Open Source Microsoft

NVIDIA AMD arm Qualcomm

HUAWEI intel IBM

Unframeworks

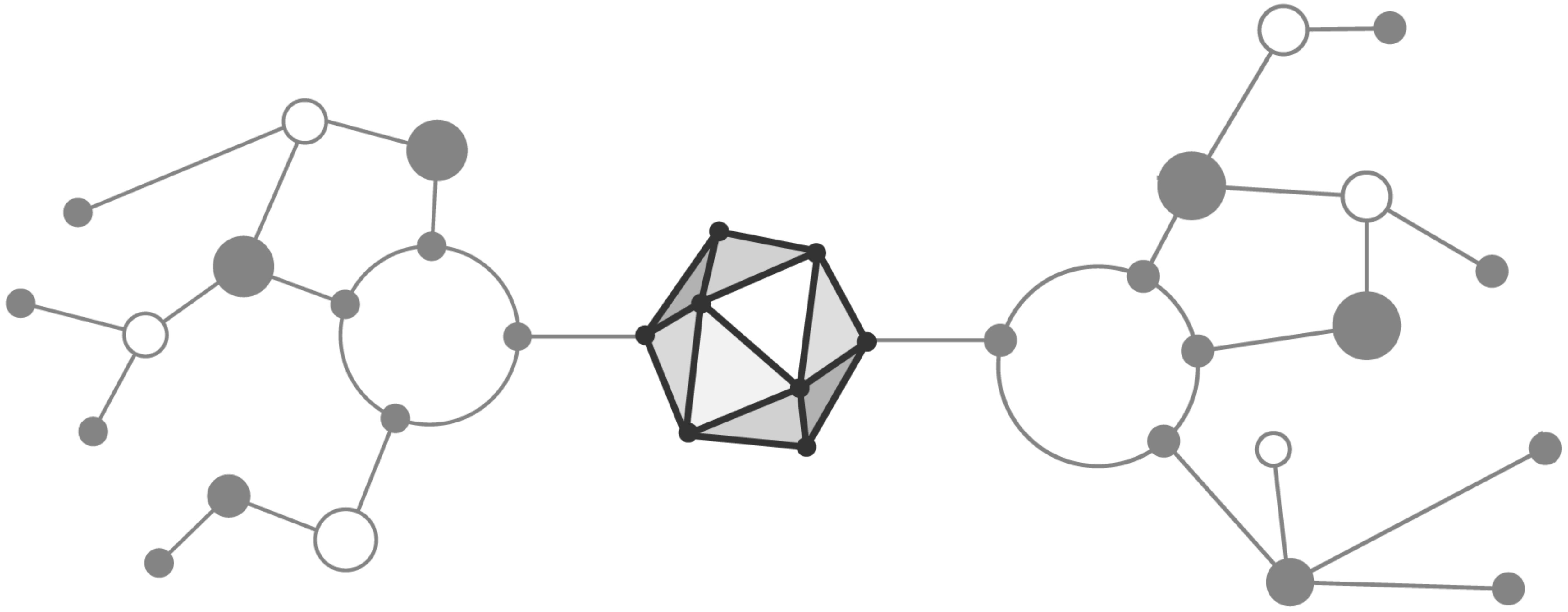
Unframeworks

Vision: Interoperable Tools

- Accelerate research to production
- Developers can use the best combination of tools for them
- Enables more people to contribute

Approach:

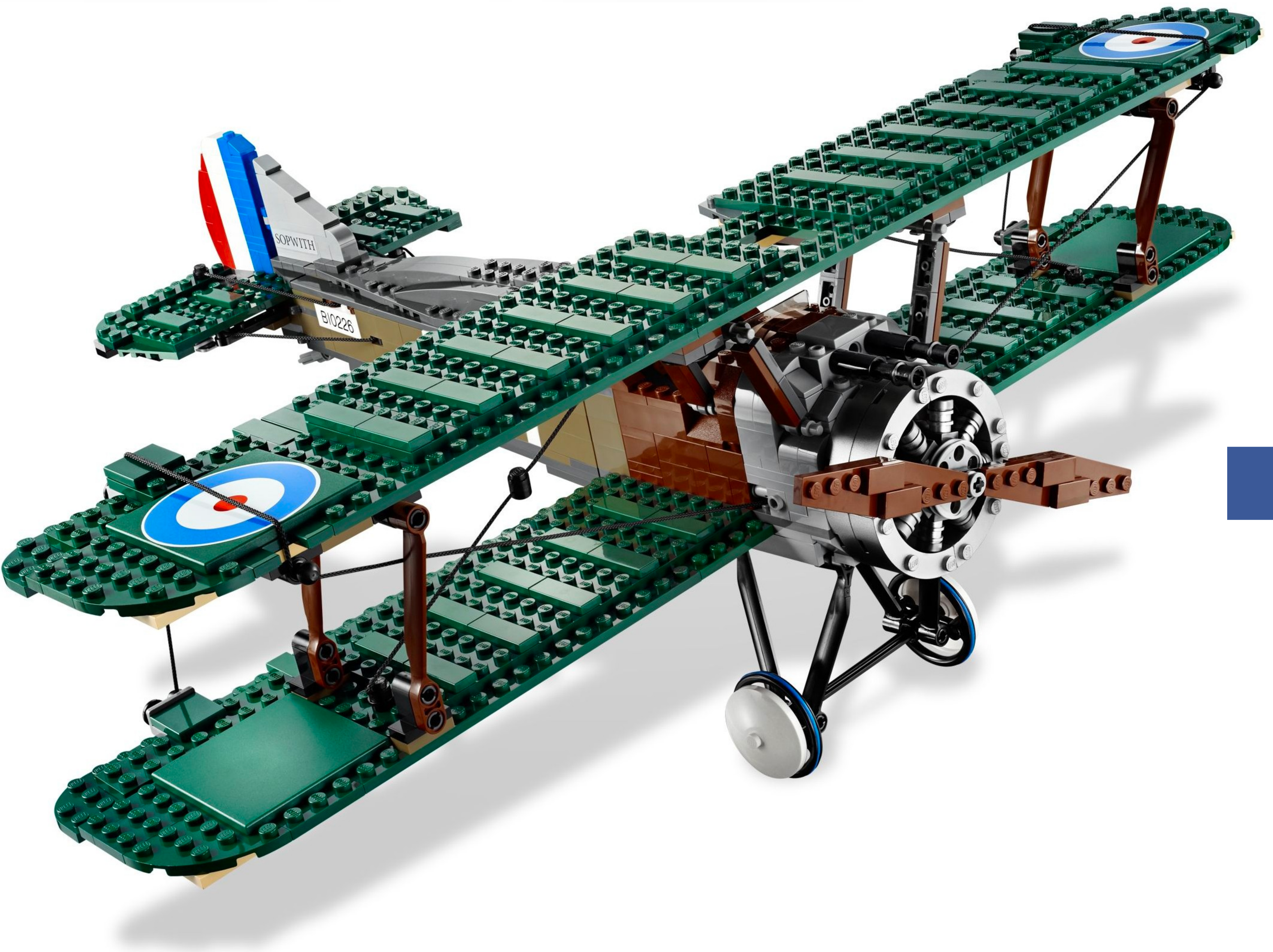
- Split toolchain into smaller components



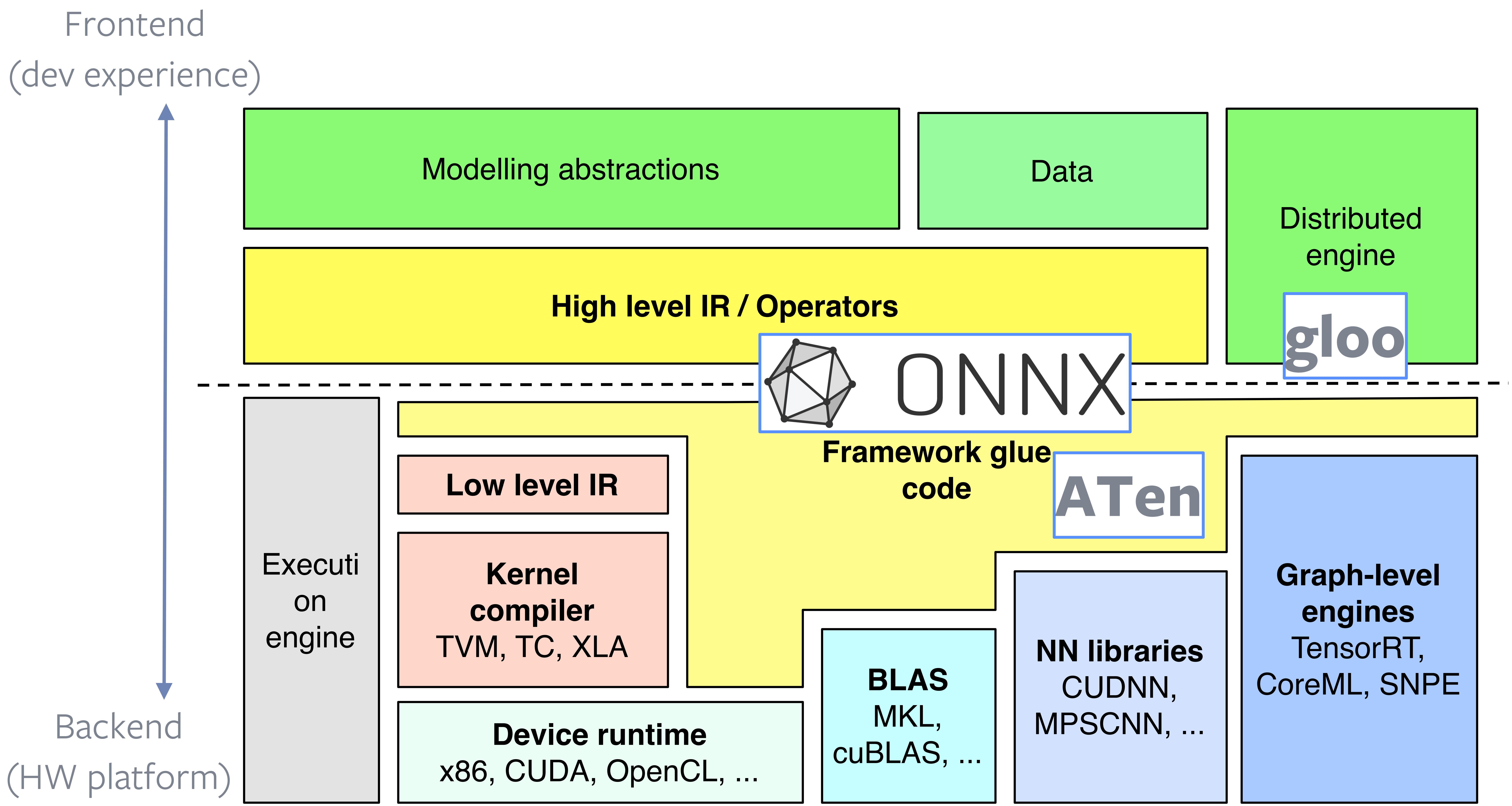
UNIX philosophy for deep learning frameworks

Build reusable components that work well together

(across frameworks)

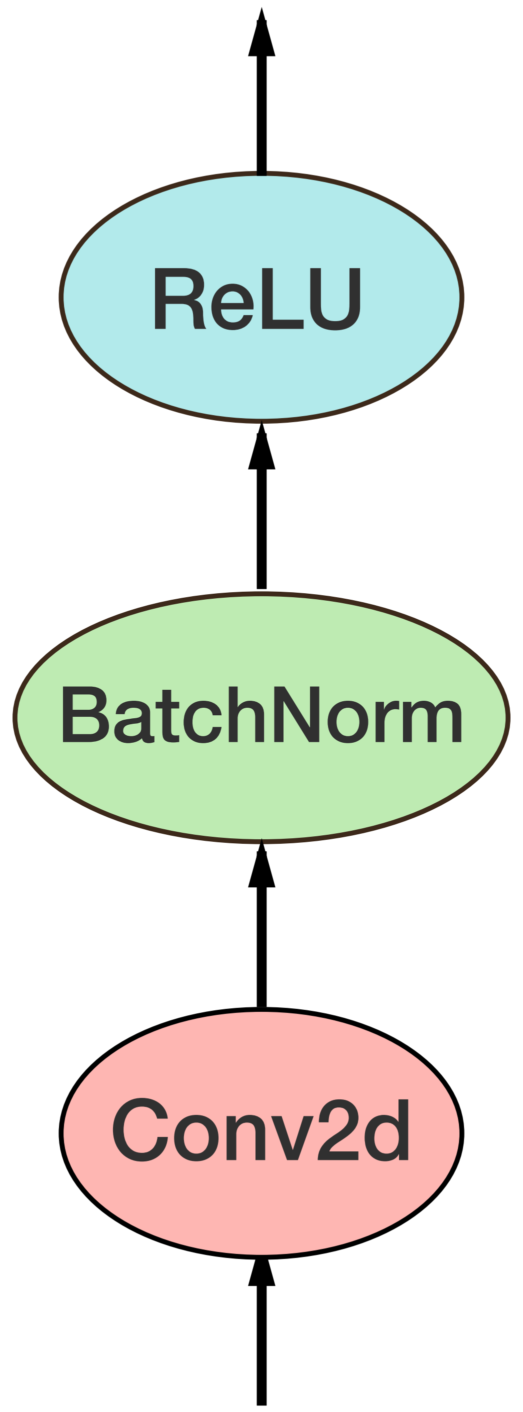


Framework anatomy



ONNX high-level IR

- Initial focus on exchange for inference
- **SSA graph structure, serializable**
  - Support for structured control flow
- **Standard operator definitions**
  - Striking balance on granularity
  - Codified semantics in tests/ref
- **Common optimization passes**



PRelu

PRelu takes input data (Tensor) and slope tensor as input, and produces one output data (Tensor) where the fu
`f(x) = slope * x for x < 0`, `f(x) = x for x >= 0`., is applied to the data tensor elementwise.

Inputs

`X` : *T*
Input tensor

`Slope` : *T*
Slope tensor. If `Slope` is of size 1, the value is sharedacross different channels

Outputs

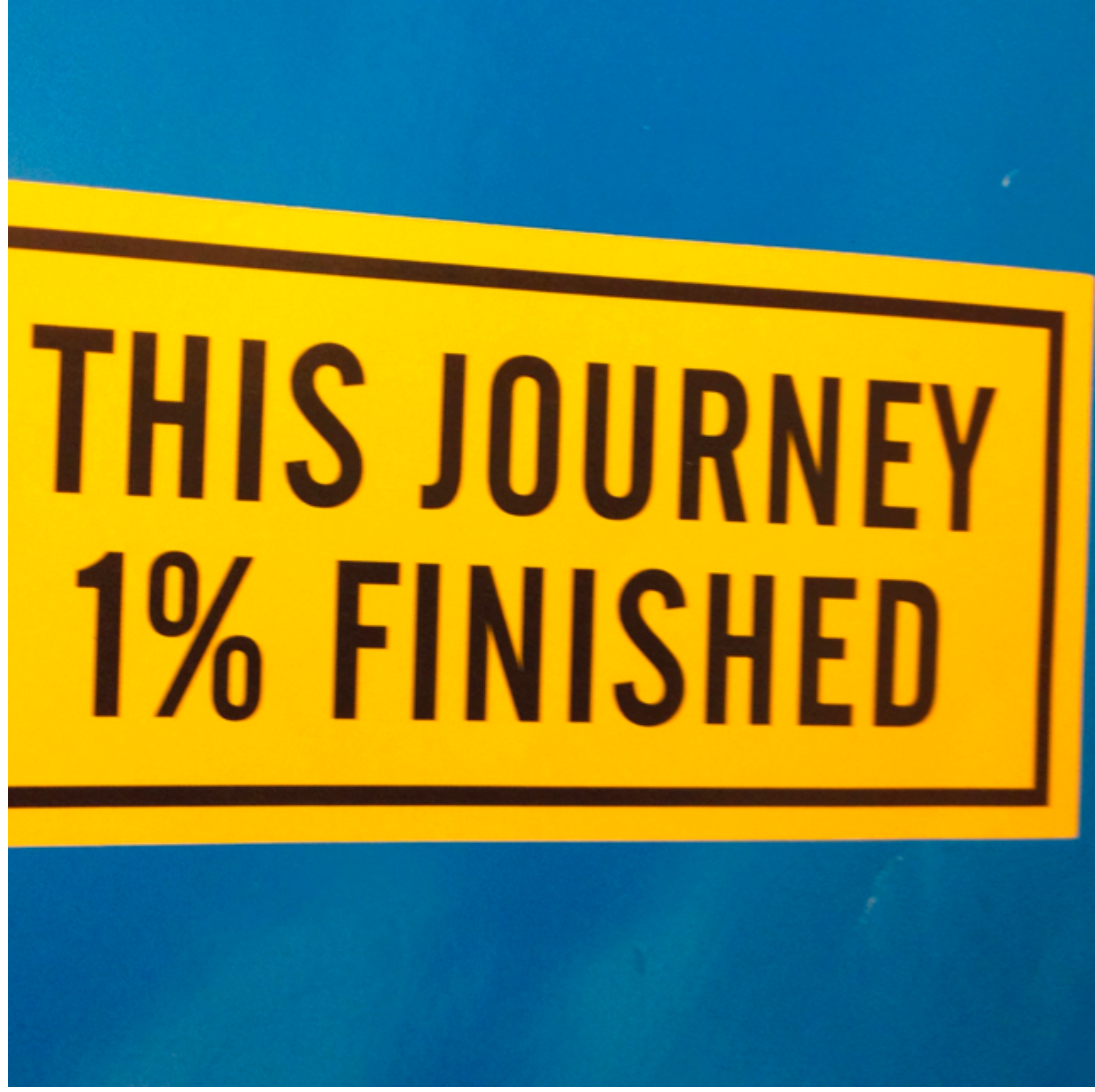
`Y` : *T*
Output tensor

Type Constraints

`T` : ***tensor(float16), tensor(float), tensor(double)***
Constrain input and output types to float tensors.

Current status

- **ONNX IR spec is V1.0**
- Good coverage for **vision** models
- Iterating on:
  - Optimization-friendly RNNs
  - Control Flow
  - More hardware backends

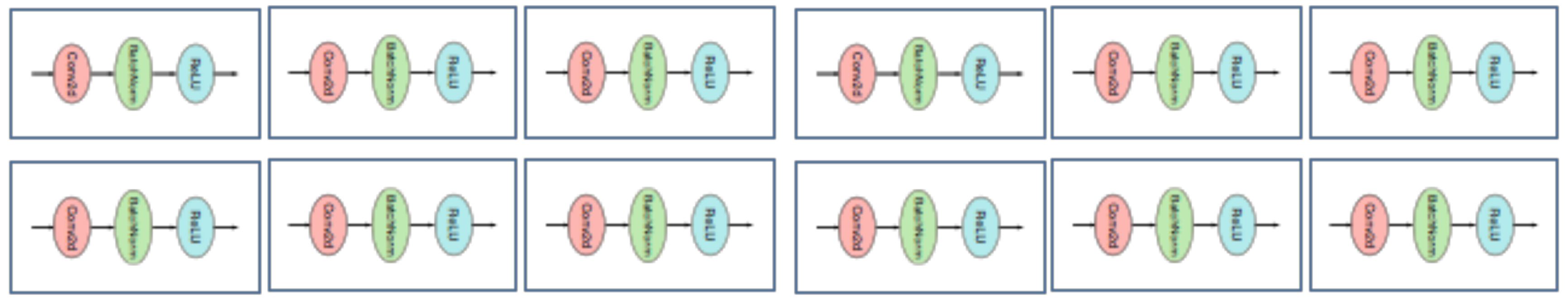


Beyond static graphs: Capturing dynamic behavior

Declarative vs Eager mode

Python script

Building IR
in Python



Python-independent
execution

Framework's VM

Operator implementations	Execution engine

Caffe2

Python interpreter

Code

Operator
implementations

Regular python extension

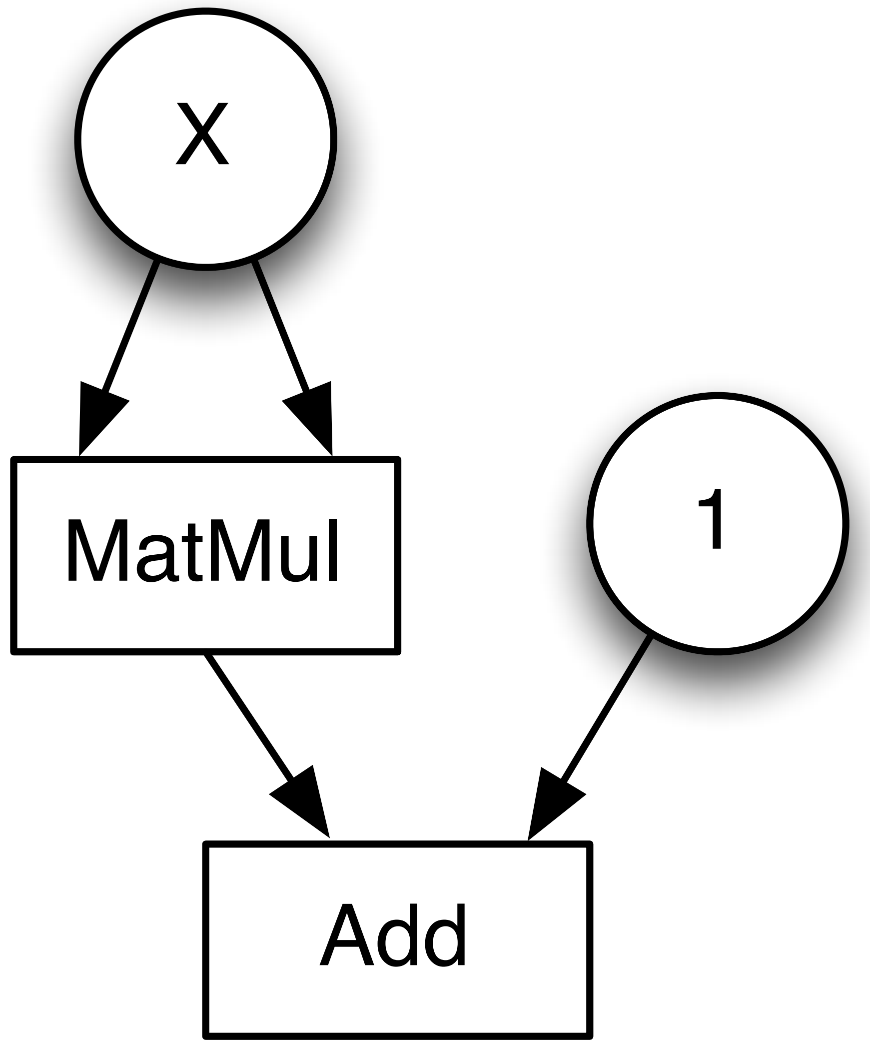
PYTORCH

Tracing for static graph

Record which operators were invoked

```python
def foo(x):
    y = x.mm(x)
   print(y) # still works!
   return y + 1

x = torch.Tensor([[1,2],[3,4]])
foo(x)
```



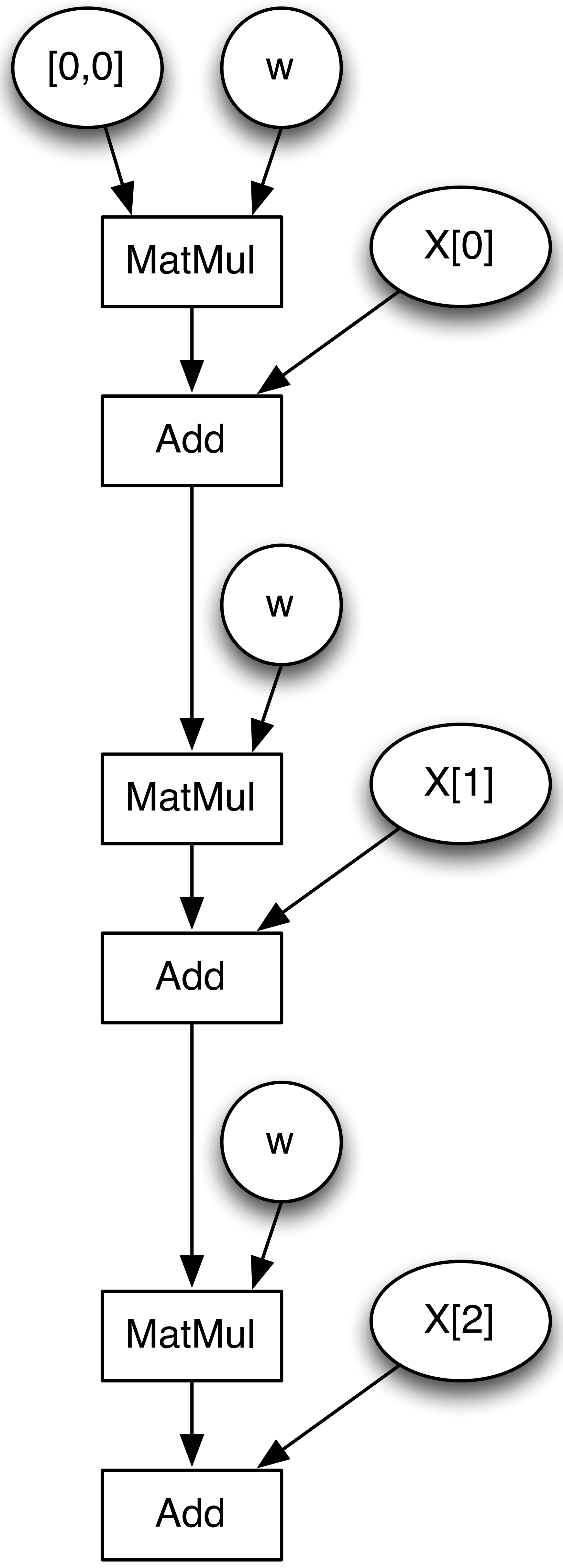
Enough to cover CNNs and static sections

Tracing for dynamic graphs

```
def foo(x, w):
    y = torch.zeros(1, 2)
    for t in x:
        y = y.mm(w) + t
    return y

w = torch.Tensor([[0.5, 0.2], [0.1, 0.4]])
x = torch.Tensor([[1, 2], [3, 4], [5, 6]])
foo(x, w)
x2 = torch.Tensor([[7, 8], [9, 10]])
foo(x2, w)
```

Doesn’t do what you want!



Tracing for dynamic graphs

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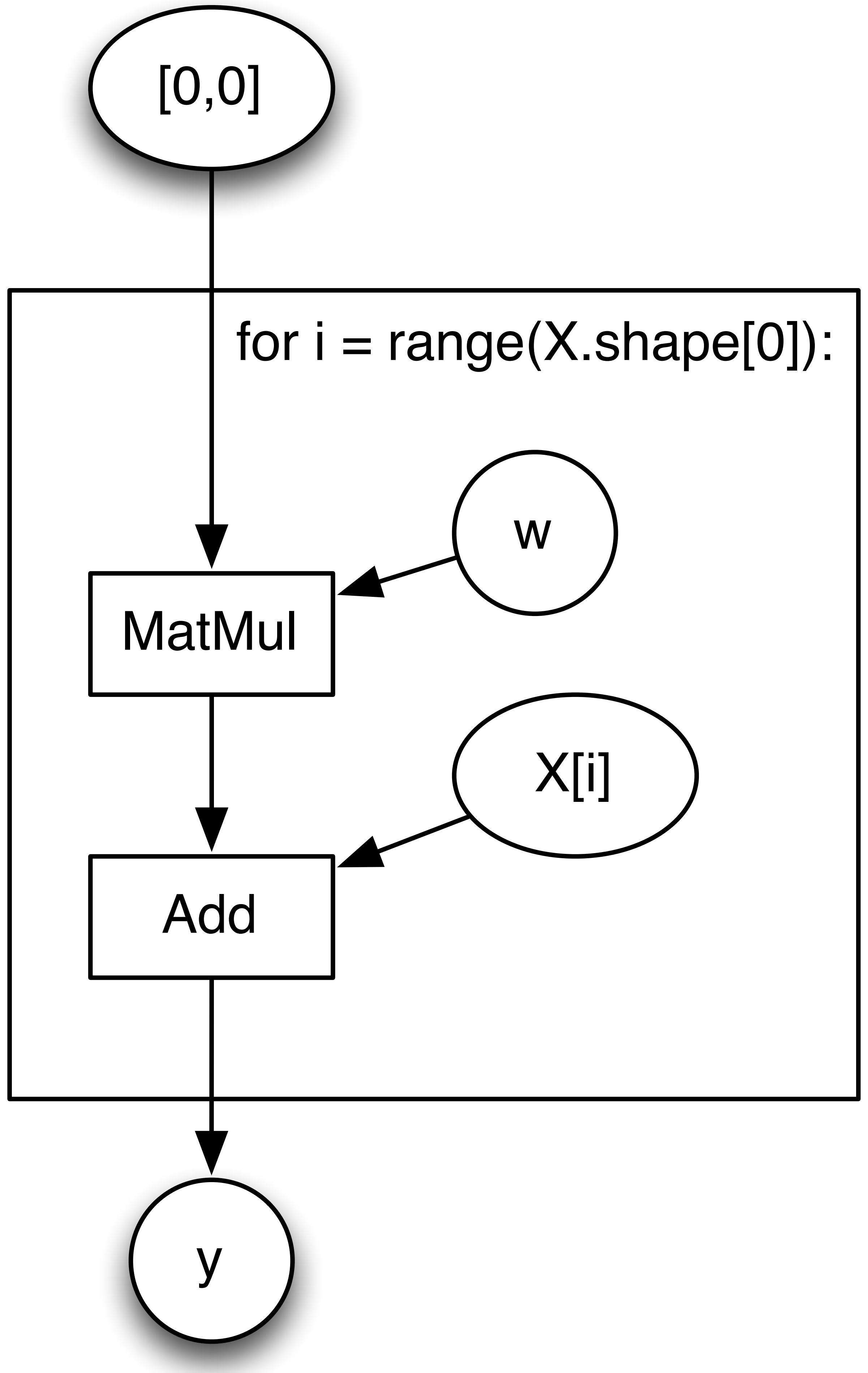

Capture control flow from python?

Approaches for dynamic graphs

- Parse or compile Python (tricky)
- Use special primitives (annoying)

```
for t in x:
  y = y.mm(w) + t
```

➡

```
lib.For(x, y, lambda y, t:
    y.mm(w) + t)
```

- Capture common patterns like RNN
- Build DSL for subset of Python
- Make it easy to embed C++ calling back to framework

Putting it together

Capturing dynamic behavior

- Trace static portions
- Minimum rewrites for dynamic parts
- Establish tooling for step-by-step code migration

ONNX Get Involved!

ONNX is a community project.

https://onnx.ai

https://github.com/onnx

aws

Facebook Open Source

Microsoft

facebook