

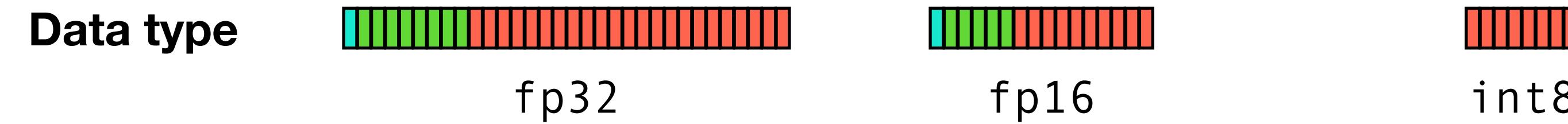
Bring Your Own Datatypes

Gus Smith
University of Washington

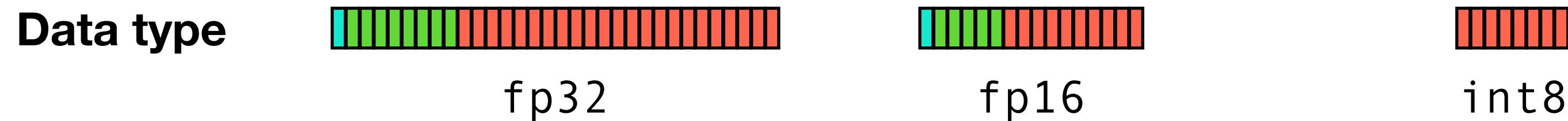


Why?

Why?



Why?



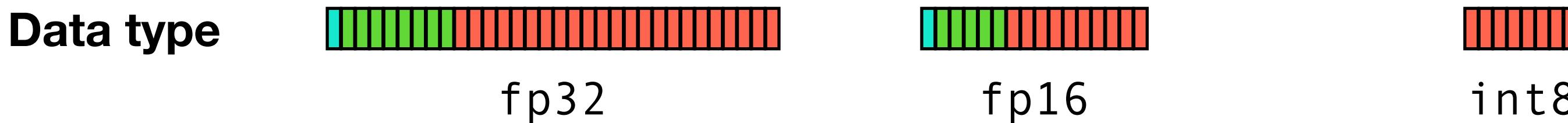
Beating Floating Point at its Own Game: Posit Arithmetic

John L. Gustafson¹, Isaac Yonemoto²

A new data type called a *posit* is designed as a direct drop-in replacement for IEEE Standard 754 floating-point numbers (floats). Unlike earlier forms of universal number (unum) arithmetic, posits do not require interval arithmetic or variable size operands; like floats, they round if an answer is inexact. However, they provide compelling advantages over floats, including larger dynamic range, higher accuracy, better closure, bitwise identical results across systems, simpler hardware, and simpler exception handling. Posits never overflow to infinity or underflow to zero, and “Not-a-Number” (NaN) indicates an action instead of a bit pattern. A posit processing unit takes less circuitry than an IEEE float FPU. With lower power use and smaller silicon footprint, the posit operations per second (POPS) supported by a chip can be significantly higher than the FLOPS using similar hardware resources. GPU accelerators and Deep Learning processors, in particular, can do more per watt and per dollar with posits, yet deliver superior answer quality.

A comprehensive series of benchmarks compares floats and posits for decimals of accuracy produced for a set precision. Low precision posits provide a better solution than “approximate

Why?



Beating Floating Point at its Own Game
John L. Gustafson¹, Isaac Yonemoto²

A new data type called a *posit* is designed as a replacement for the IEEE 754 floating-point numbers (floats). Unlike earlier floating-point formats, posits do not require interval arithmetic or variable rounding. While the IEEE standard answer is inexact, they provide compelling advantages: a wider dynamic range, higher accuracy, better closure, bitwise identity, and simpler exception handling. Posits never overflow or underflow. A “Not-a-Number” (NaN) indicates an action instead of a value. Posits require less circuitry than an IEEE float FPU. With lower power consumption and more operations per second (POPS) supported by a chip using similar hardware resources, GPU accelerators can do more per watt and per dollar with posits, yet cost less.

A comprehensive series of benchmarks comparing posits produced for a set precision. Low precision posits

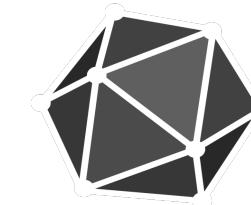
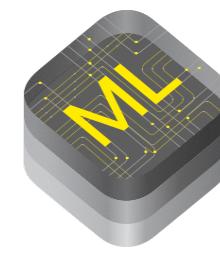
Rethinking floating point for deep learning

Jeff Johnson
Facebook AI Research
New York, NY
jhj@fb.com

Abstract

Reducing hardware overhead of neural networks for faster or lower power inference and training is an active area of research. Uniform quantization using integer multiply-add has been thoroughly investigated, which requires learning many quantization parameters, fine-tuning training or other prerequisites. Little effort is made to improve floating point relative to this baseline; it remains energy ineffi-

The Goal: BYO-Datatype



High-Level Differentiable IR

Tensor Expression IR

LLVM, CUDA, Metal

VTA

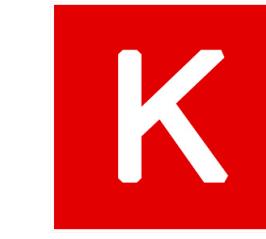
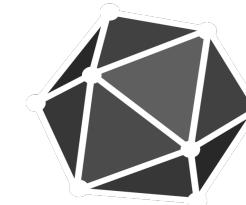
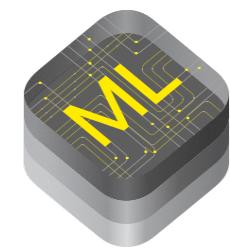


Edge
FPGA

Cloud
FPGA

ASIC

The Goal: BYO-Datatype



+ **your custom
datatypes!**

High-Level Differentiable IR

Tensor Expression IR

LLVM, CUDA, Metal

VTA

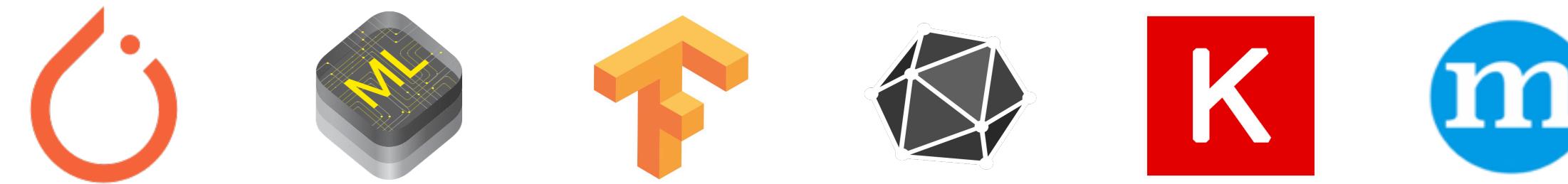


Edge
FPGA

Cloud
FPGA

ASIC

The Goal: BYO-Datatype



+ **your custom datatypes!**

High-Level Differentiable IR

Tensor Expression IR



+ other datatype libraries

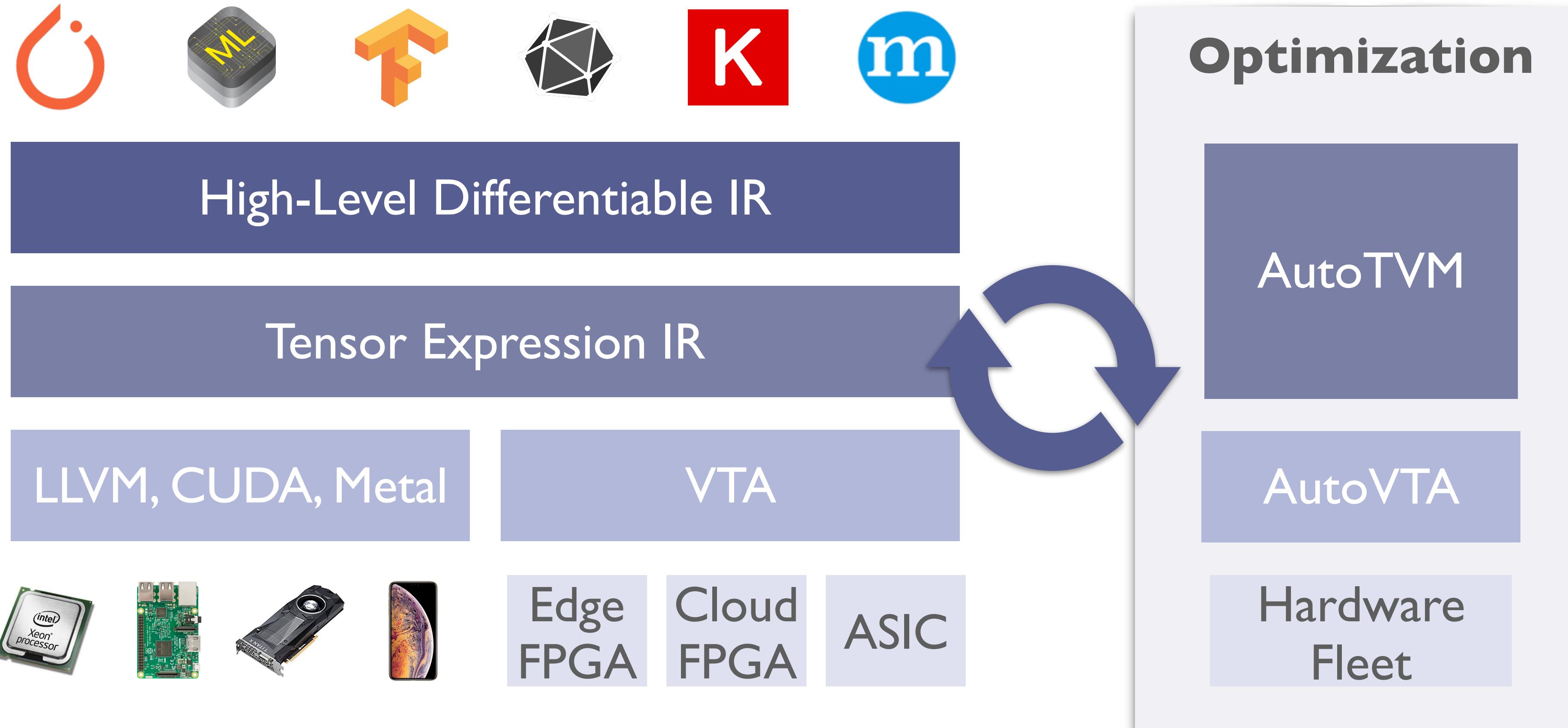


LLVM, CUDA, Metal

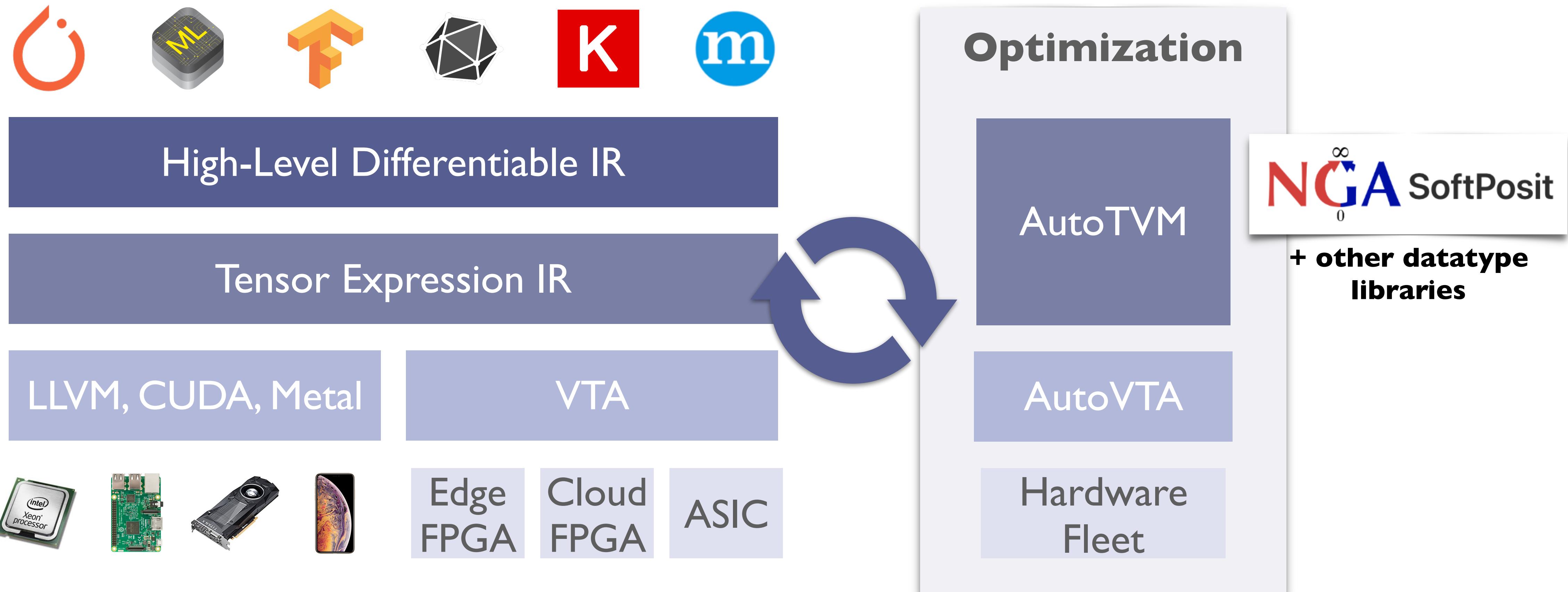
VTA

Edge FPGA
Cloud FPGA
ASIC

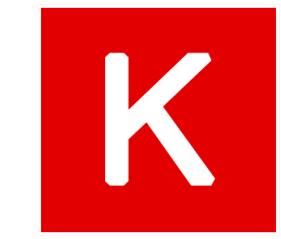
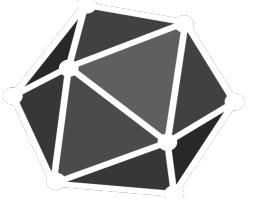
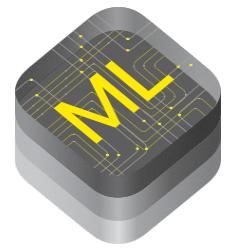
The Goal: BYO-Datatype



The Goal: BYO-Datatype



Future Directions: Hardware



High-Level Differentiable IR

Tensor Expression IR

LLVM, CUDA, Metal

VTA

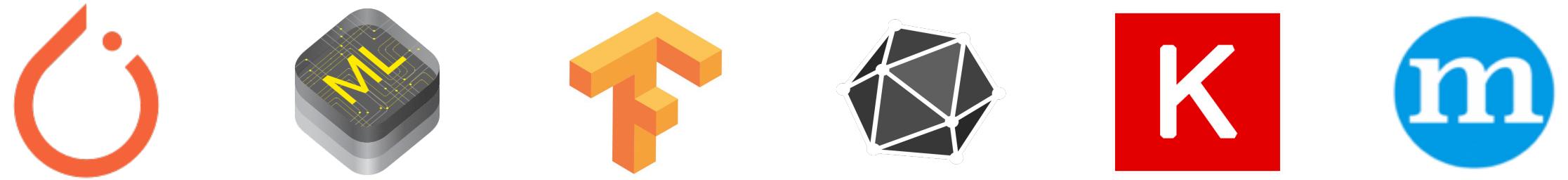


Edge
FPGA

Cloud
FPGA

ASIC

Future Directions: Hardware



High-Level Differentiable IR

Tensor Expression IR

LLVM, CUDA, Metal

VTA



 [facebookresearch / deepfloat](#)

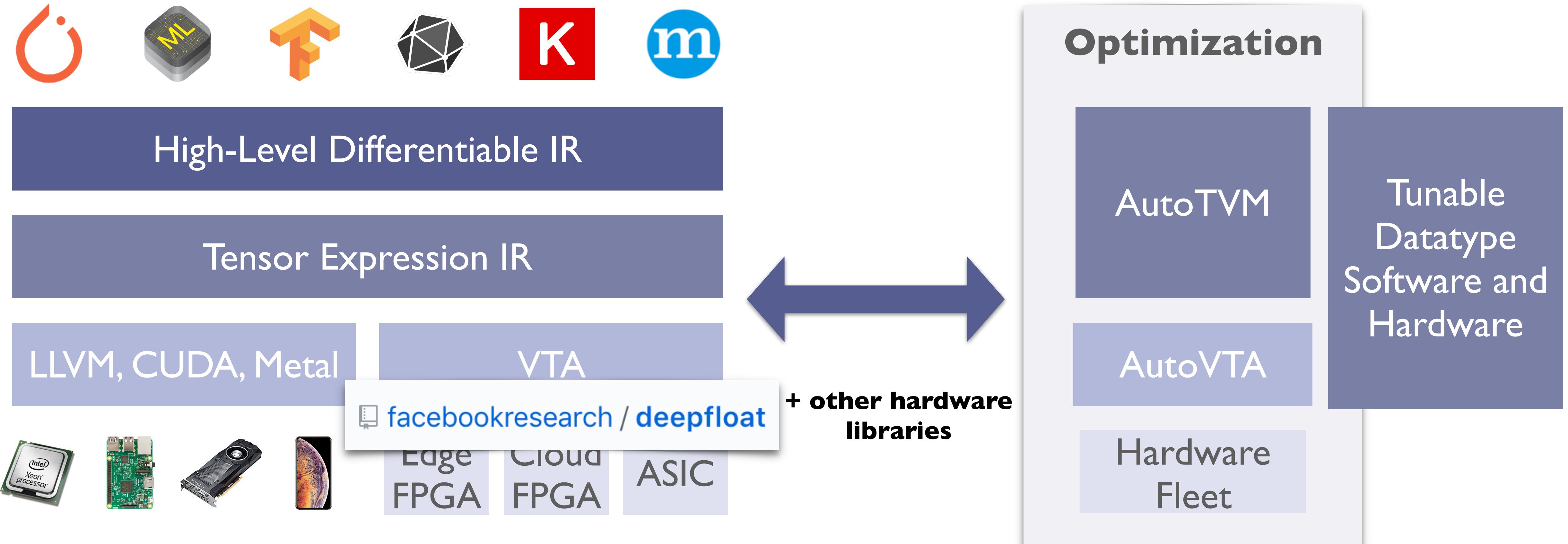
Edge
FPGA

Cloud
FPGA

ASIC

+ other hardware
libraries

Future Directions: Hardware



What it Looks Like Today

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")
```

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")

cast = tvm.build(flist[0], target=tgt)
```

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")

cast = tvm.build(flist[0], target=tgt)

x = tvm.nd.array(np.random.uniform(size=3).astype(X.dtype), ctx)
y = tvm.nd.empty(Y.shape, dtype=Y.dtype, ctx=ctx)
```

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")

cast = tvm.build(flist[0], target=tgt)

x = tvm.nd.array(np.random.uniform(size=3).astype(X.dtype), ctx)
y = tvm.nd.empty(Y.shape, dtype=Y.dtype, ctx=ctx)

cast(x,y)
```

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")

cast = tvm.build(flist[0], target=tgt)

x = tvm.nd.array(np.random.uniform(size=3).astype(X.dtype), ctx)
y = tvm.nd.empty(Y.shape, dtype=Y.dtype, ctx=ctx)

cast(x,y)
```

Defining lowering from our custom datatype in C++:

```
TVM_REGISTER_GLOBAL("tvm.datatypes.lower.llvm.cast.myfloat.float")
.set_body([](runtime::TVMArgs args, runtime::TVMReturnValue *rv) {
    Expr e = args[0];
    const ir::Cast* cast = e.as<ir::Cast>();
    internal_assert(cast);
    auto type = cast->type;
    *rv = reinterpret(tvm::UInt(type.bits(), type.lanes()), cast->value);
})
```

What it Looks Like Today

Adding a custom datatype in Python:

```
tvm.register_datatype("myfloat", 24)

X = tvm.placeholder((3,), name="X")
Y = topi.cast(X, dtype="custom[myfloat]32")

cast = tvm.build(flist[0], target=tgt)

x = tvm.nd.array(np.random.uniform(size=3).astype(X.dtype), ctx)
y = tvm.nd.empty(Y.shape, dtype=Y.dtype, ctx=ctx)

cast(x,y)
```

Defining lowering from our custom datatype in C++:

```
TVM_REGISTER_GLOBAL("tvm.datatypes.lower.llvm.cast.myfloat.float")
.set_body([](runtime::TVMArgs args, runtime::TVMReturnValue *rv) {
    Expr e = args[0];
    const ir::Cast* cast = e.as<ir::Cast>();
    internal_assert(cast);
    auto type = cast->type;
    *rv = reinterpret(tvm::UInt(type.bits(), type.lanes()), cast->value);
});
```

```
x: [0.25599805 0.5752605 0.0941305 ]
y: [1048777261 1058227270 1036044158]
```

Try it out and get involved!

My TVM fork:

<https://github.com/gussmith23/tvm>

Or reach out to me at

gussmith@cs.washington.edu