Bring Your Own Datatypes: Enabling Custom Datatype Exploration in Deep Learning

Gus Smith, Qualifying Exam
February 24th, 2020

sampl

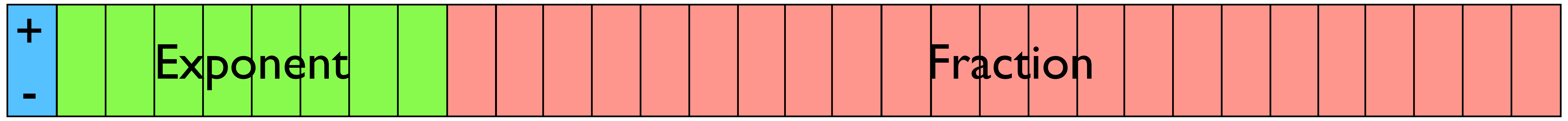
PAUL G. ALLEN SCHOOL
OF COMPUTER SCIENCE & ENGINEERING

tvm.ai

By “datatypes”, I mean **numerical datatypes:** how the hardware represents and operates on real numbers.

IEEE 754 Floating Point

Single precision (32 bit)



$$\text{value} \approx \text{sign} * 2^{\text{exponent}} * 1.\text{fraction}$$

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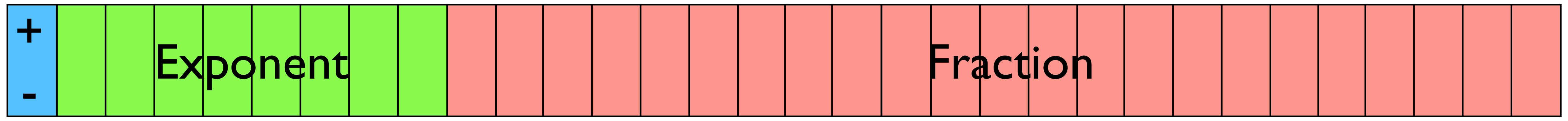

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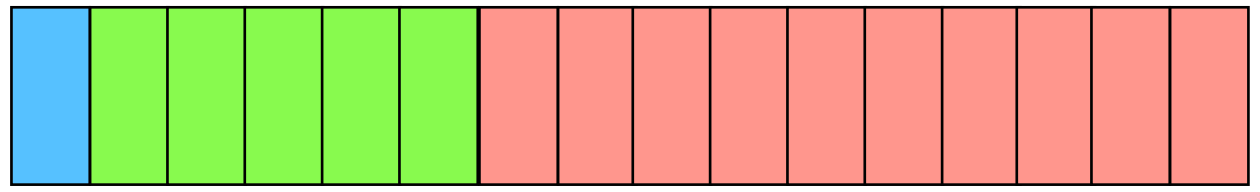
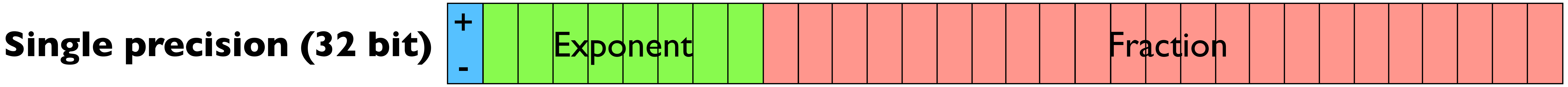
Half precision (16 bit)



IEEE 754 Floating Point



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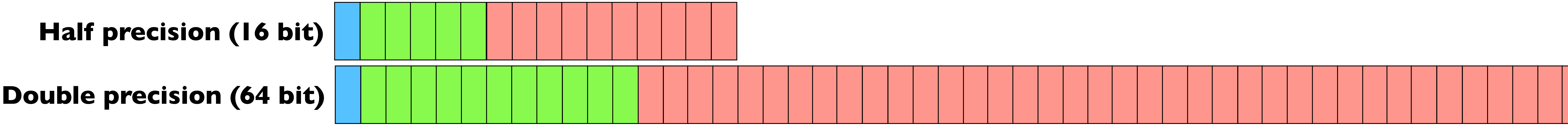

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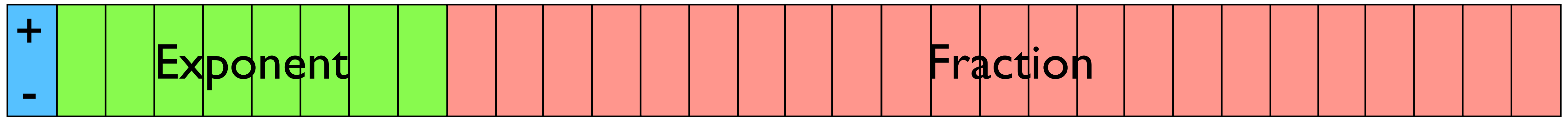

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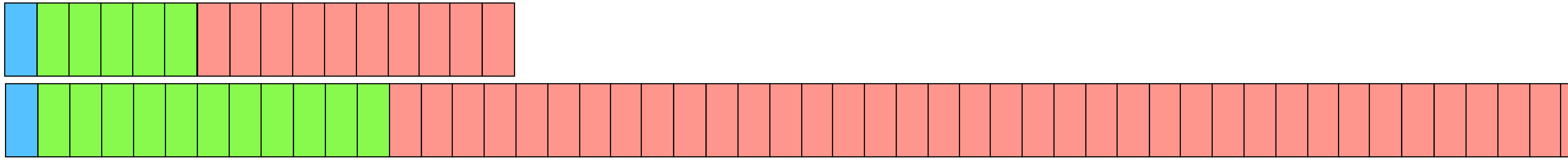
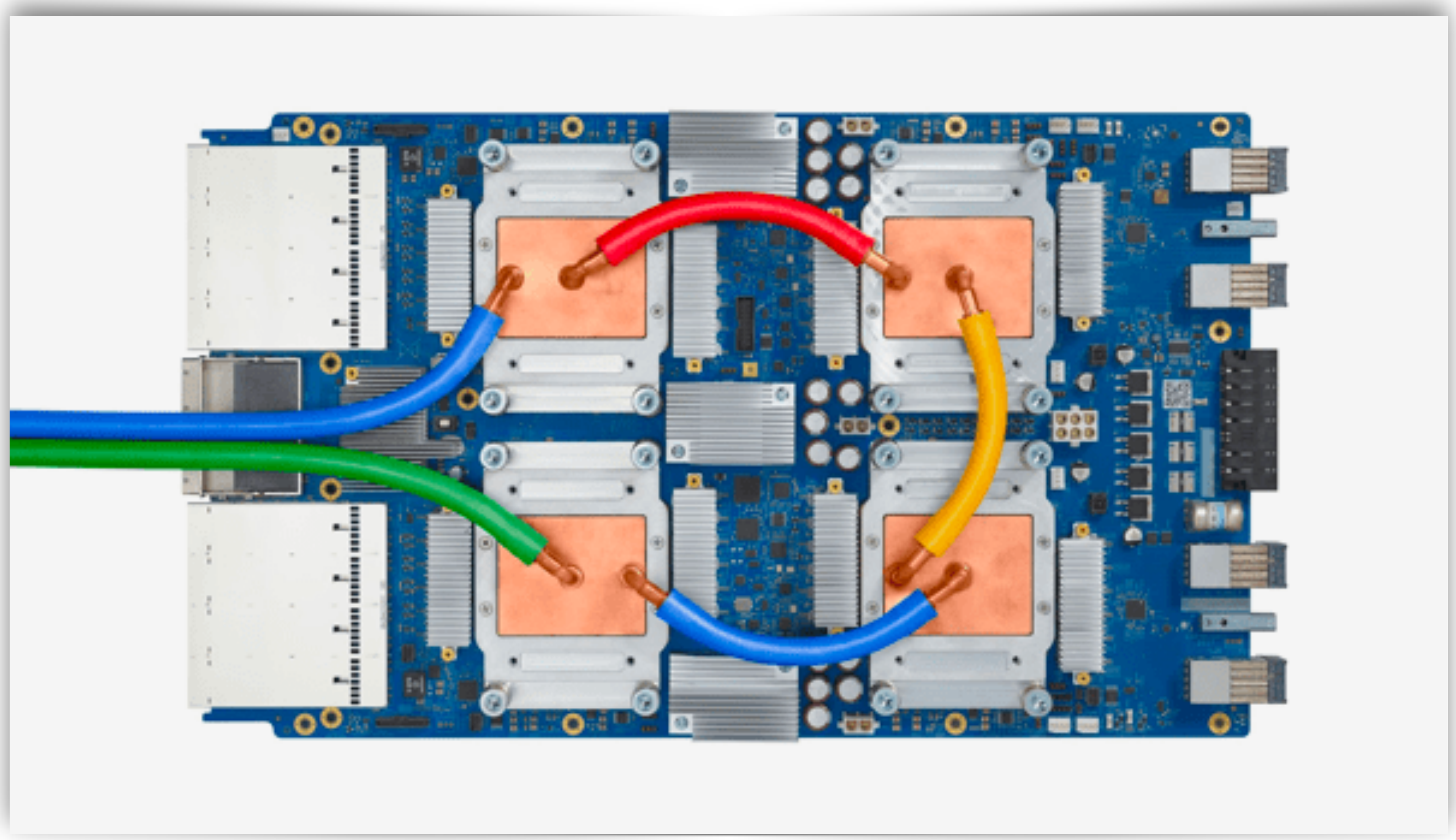
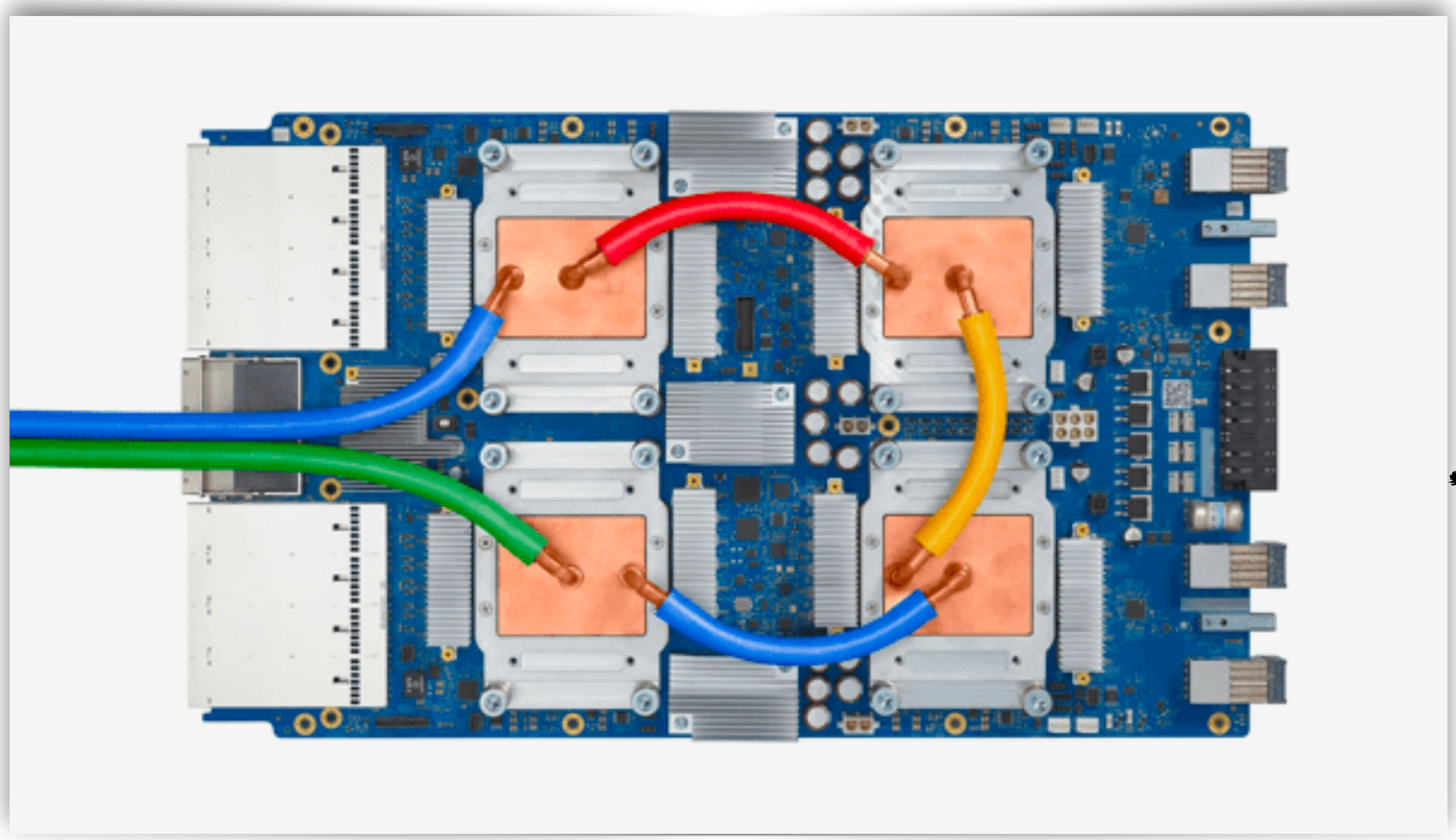
Half precision (16 bit)

Double precision (64 bit)

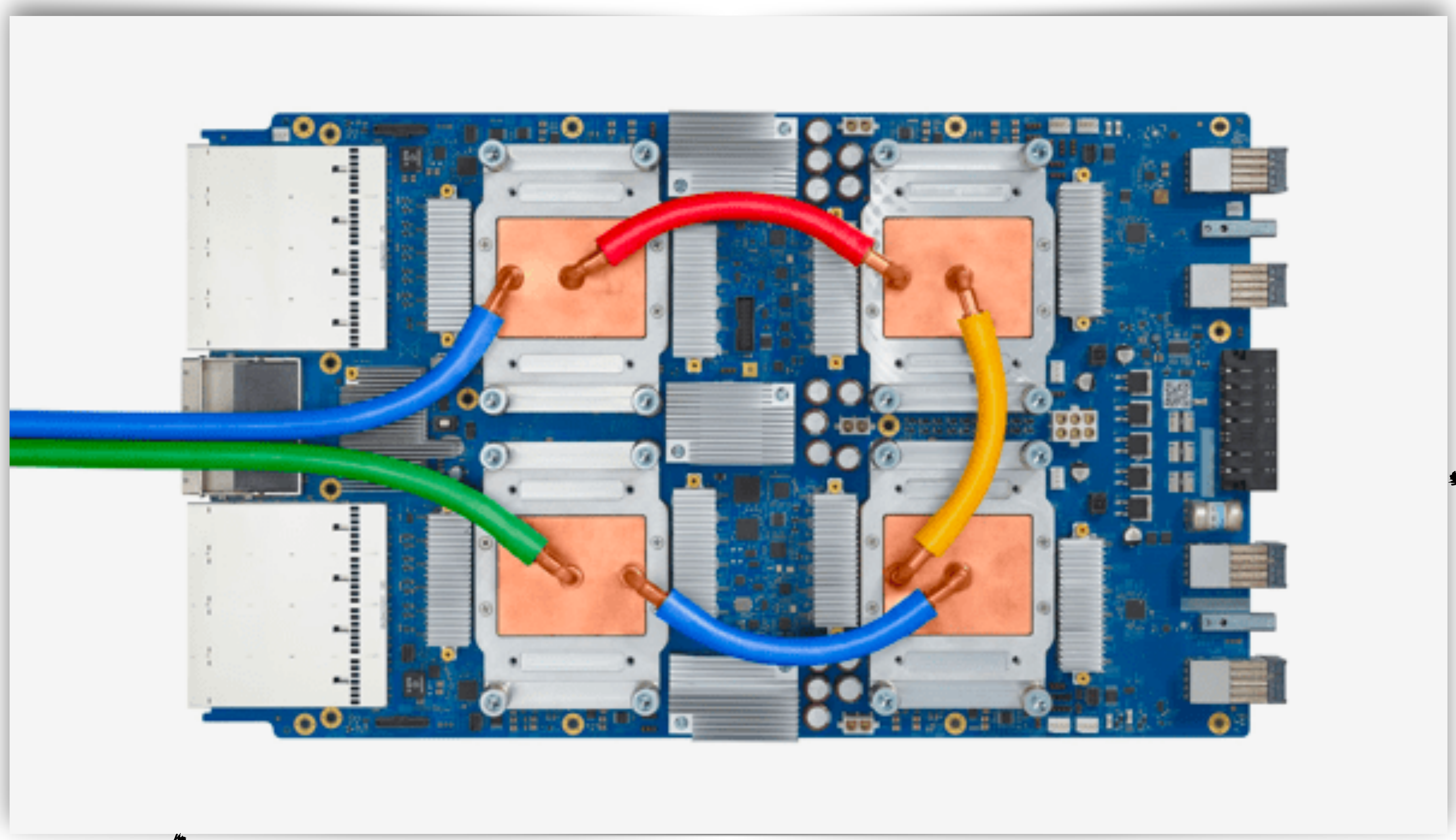


Has remained an industry standard for more than thirty years!





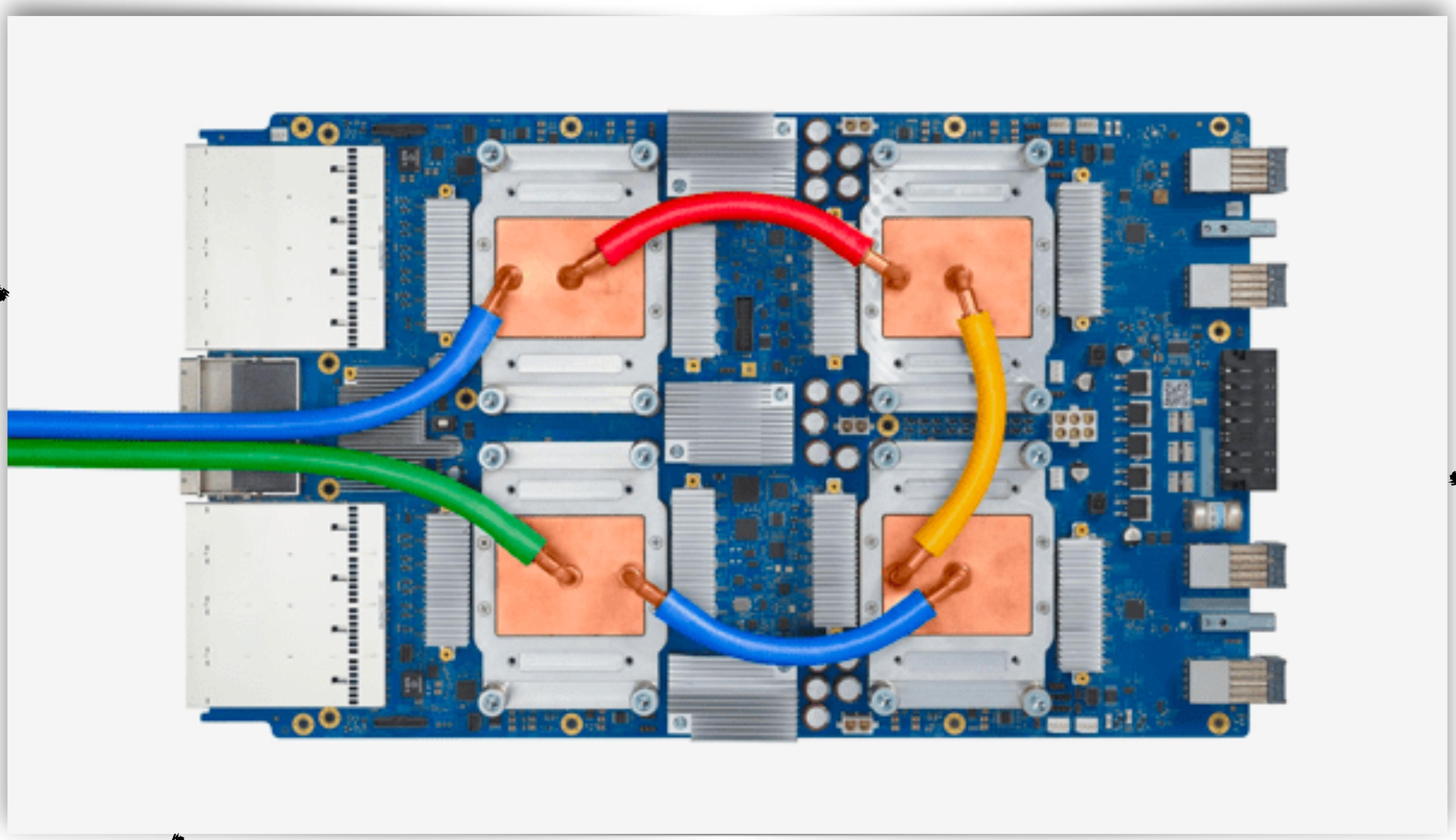
Should be fast and power-efficient



Should be fast and power-efficient

Needs small weights and activations
to maximize usage of chip area

Only needs to represent a specific range of values:
Weights and activations cluster (e.g. around [-1, 1])

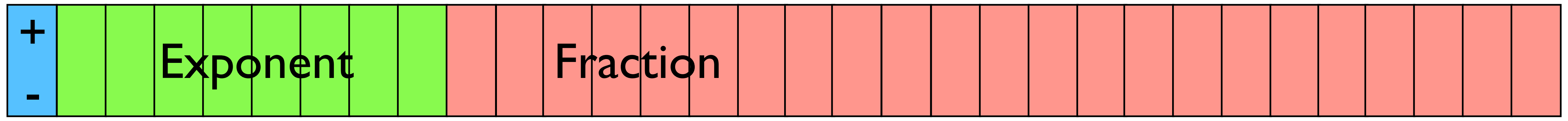


Should be fast and power-efficient

Needs small weights and activations
to maximize usage of chip area

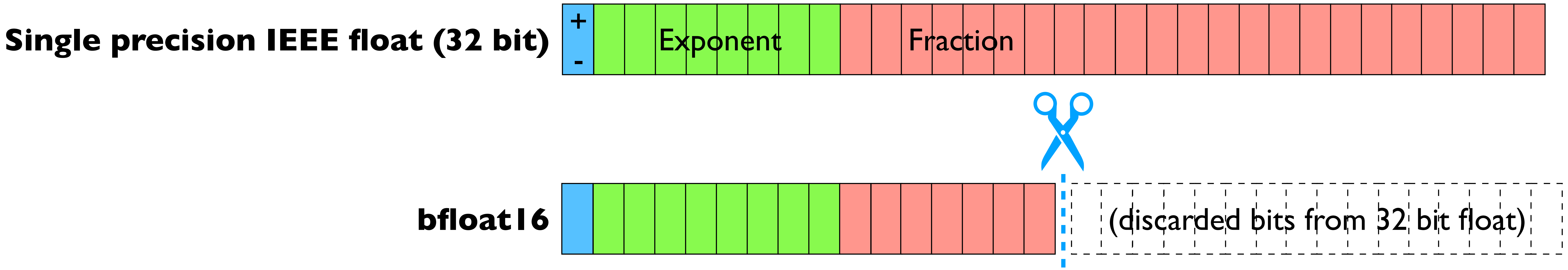
bfloat16

Single precision IEEE float (32 bit)



See https://cloud.google.com/tpu/docs/bfloat16

bfloat16



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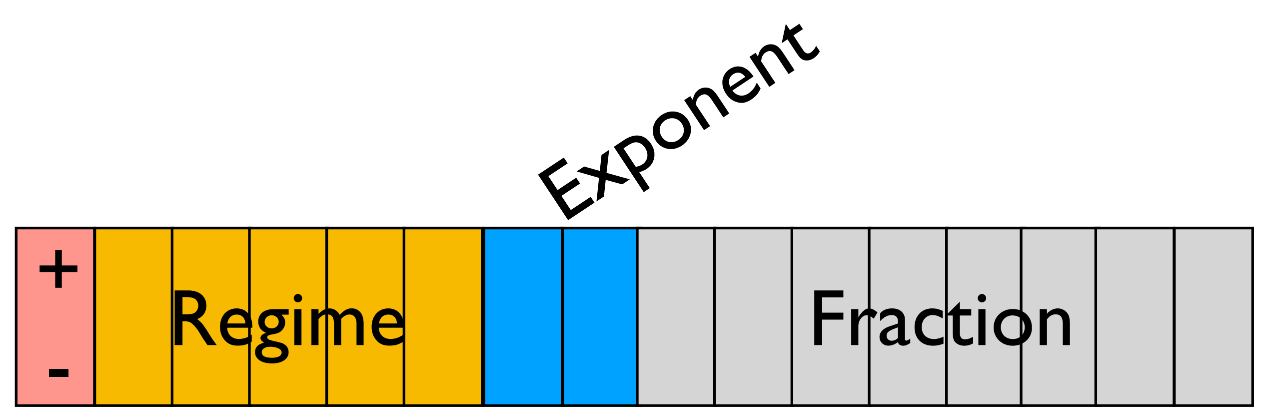
Posits



See www.johngustafson.net/pdfs/BeatingFloatingPoint.pdf

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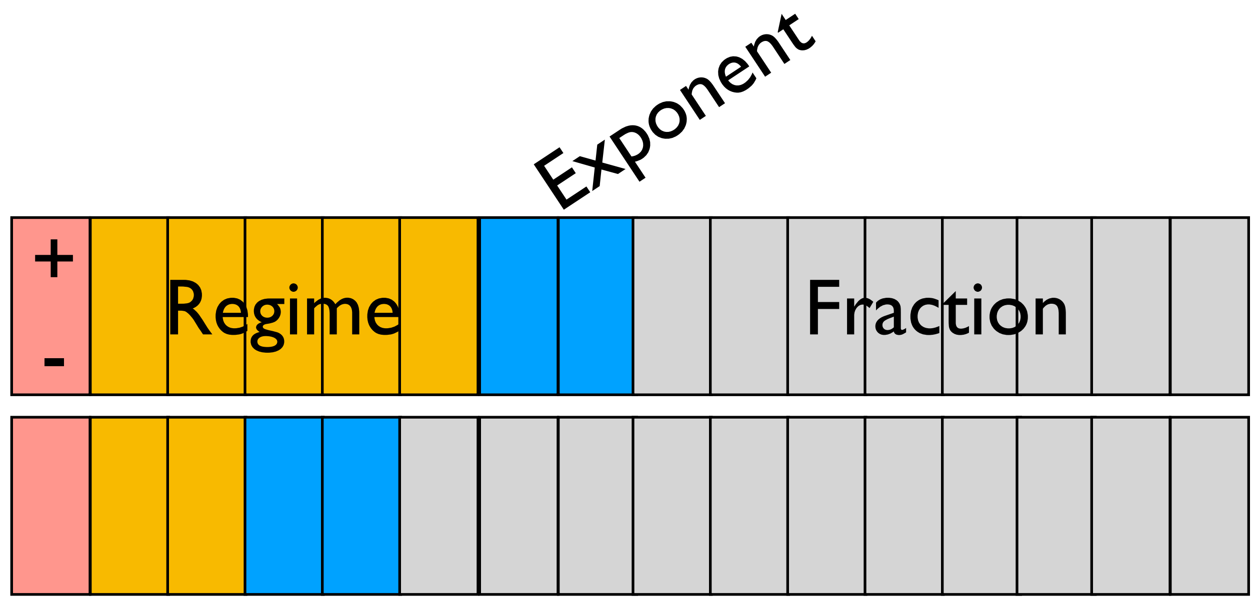

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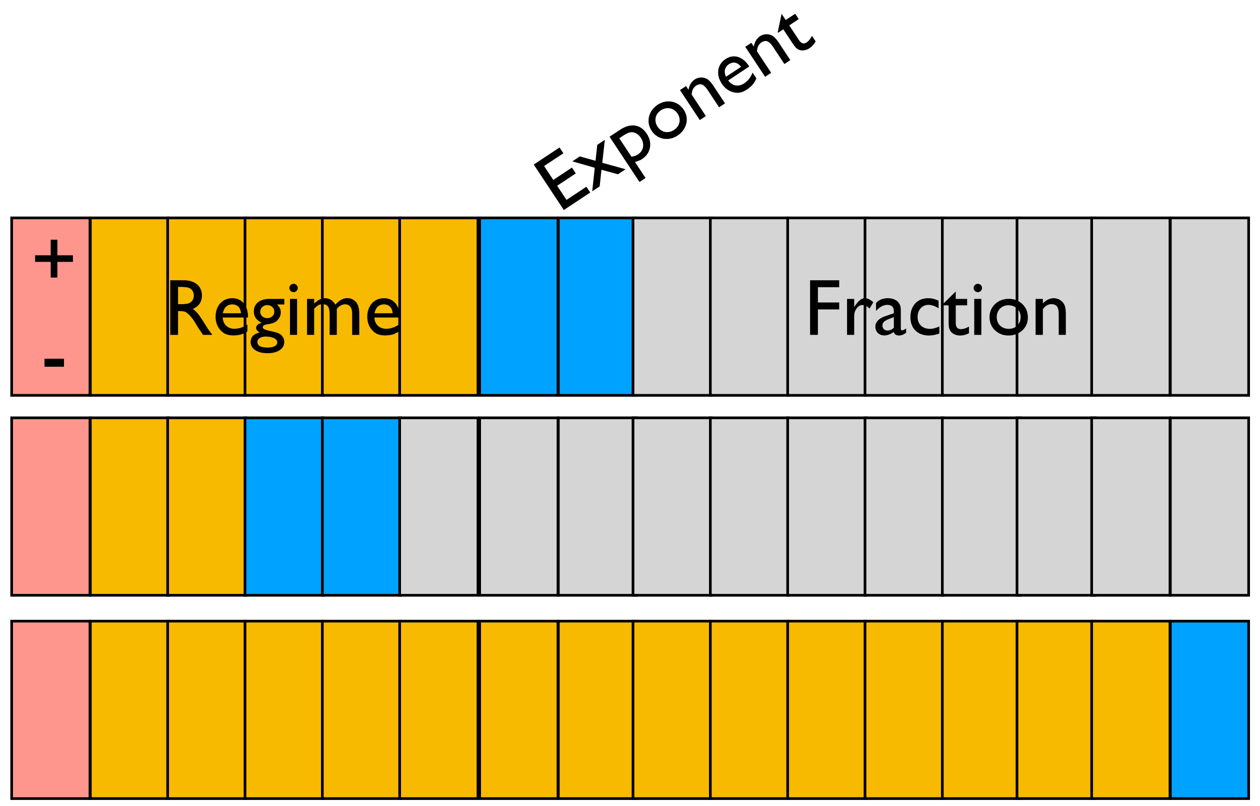

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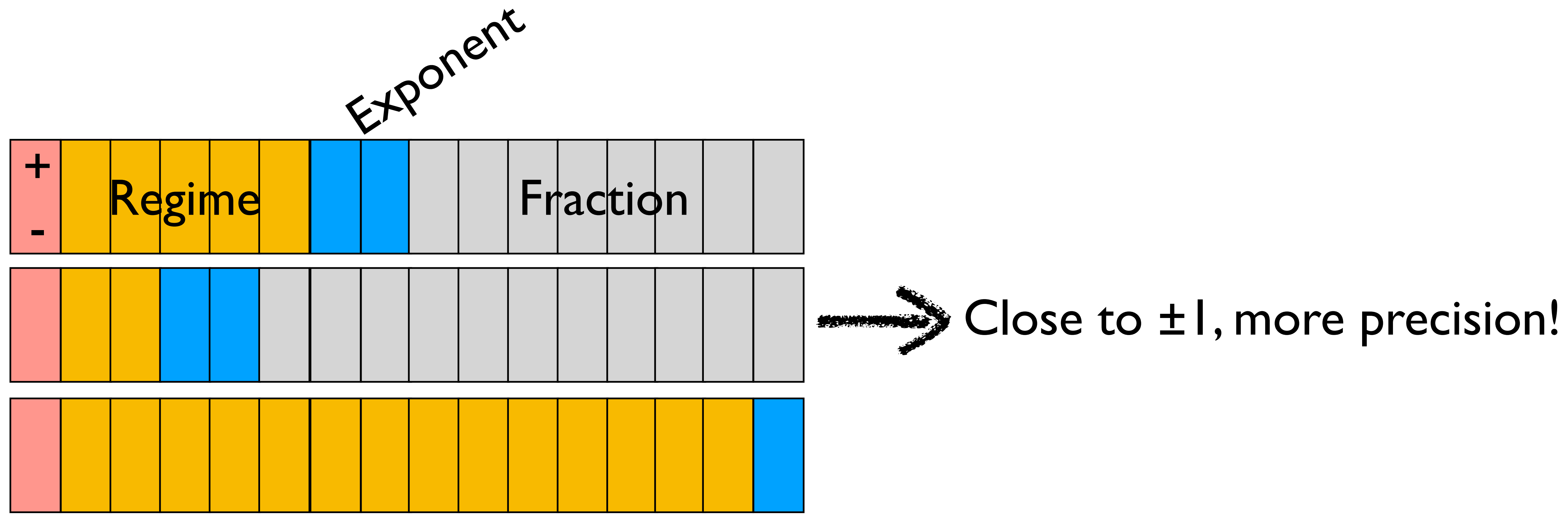

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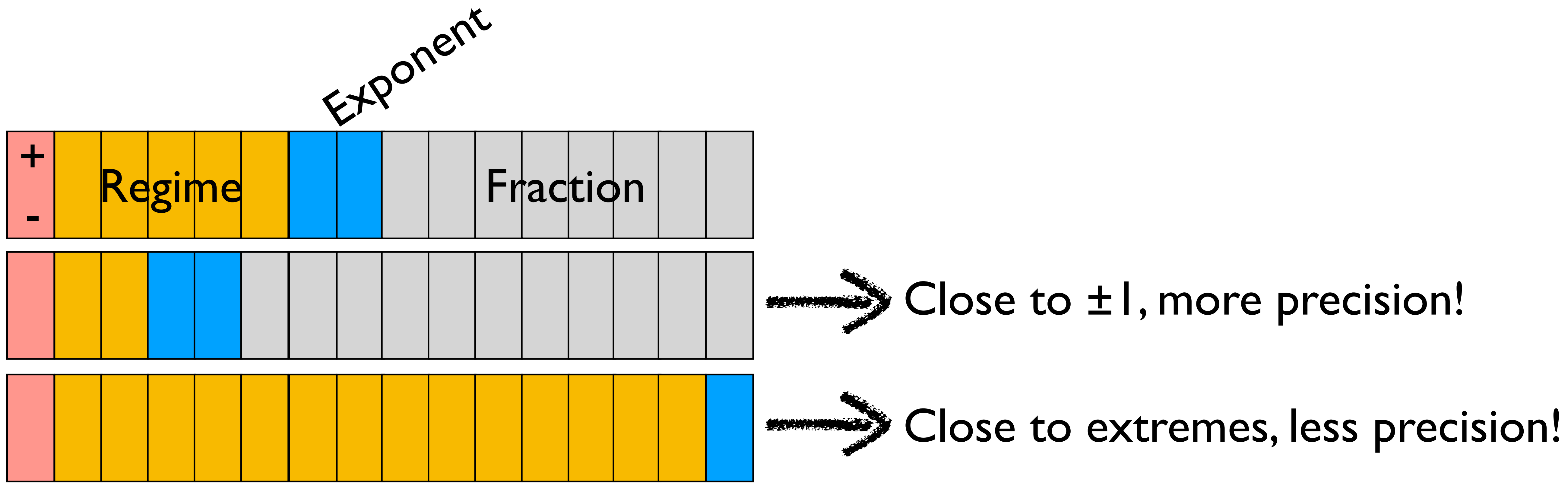

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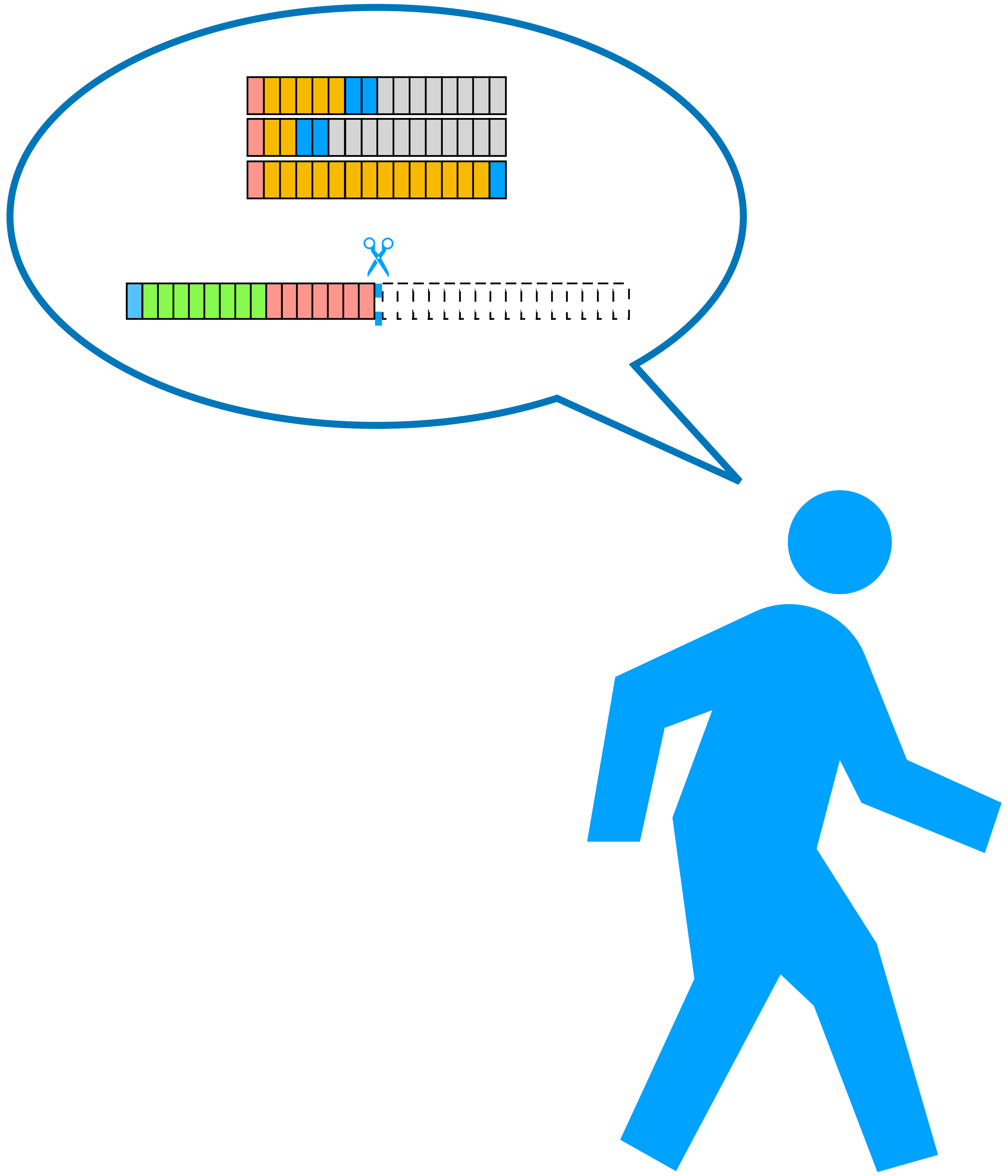
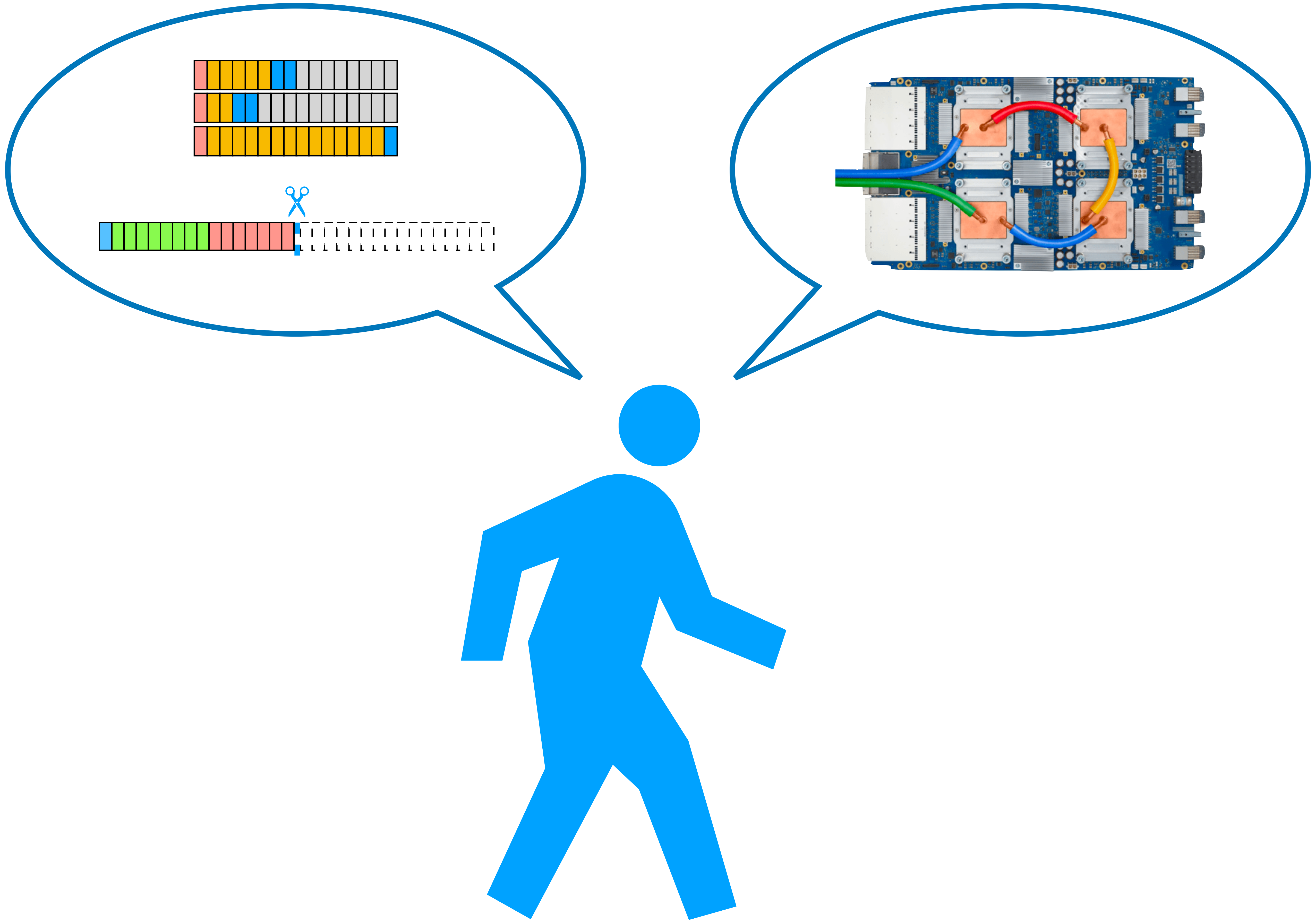
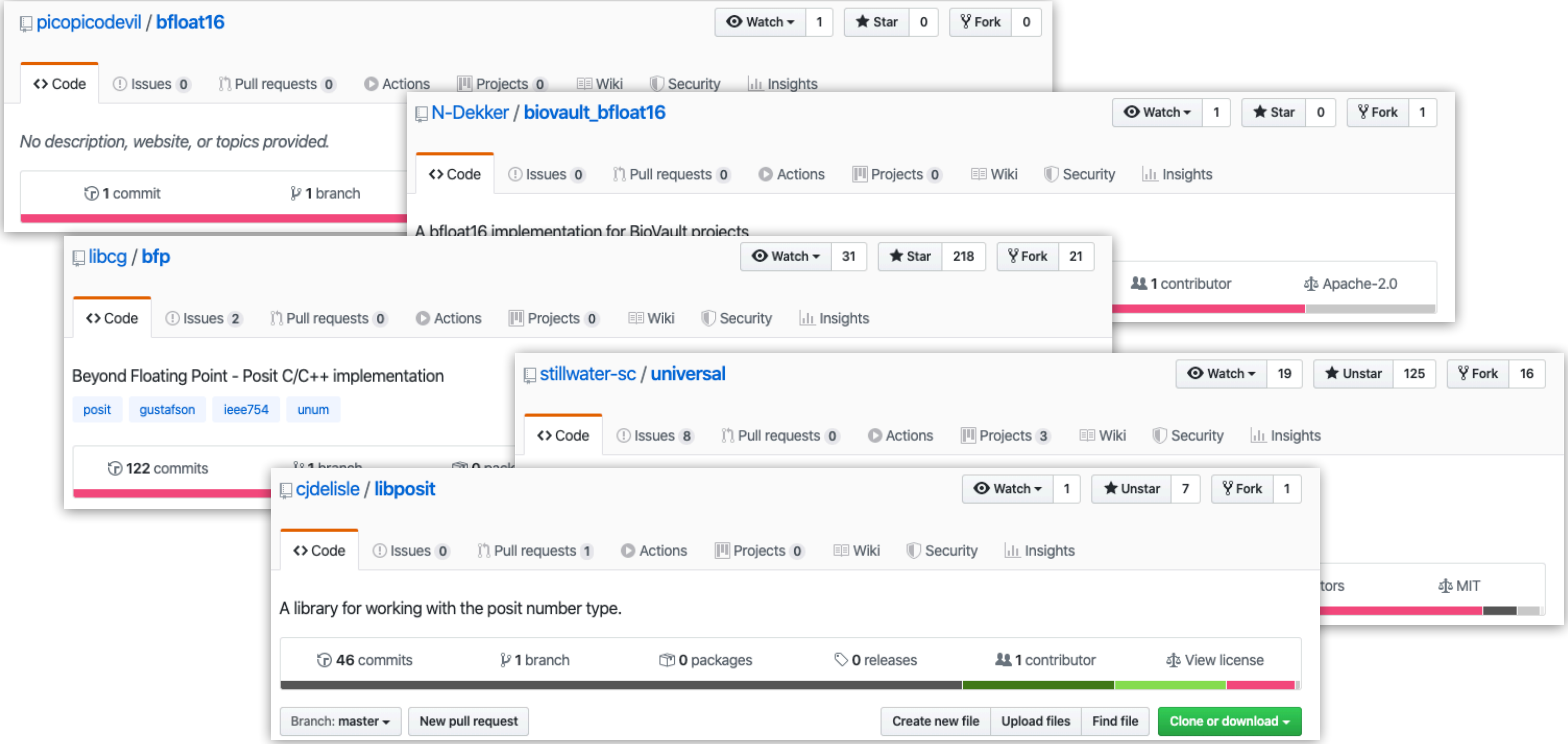
Deep learning needs hardware specialization…

Deep learning needs hardware specialization…
…and hardware specialization needs new datatypes!






picopicodevil / bfloat16
Watch 1
Star 0
Fork 0
Code
Issues 0
Pull requests 0
Actions
Projects 0
Wiki
Security
Insights
No description, website, or topics provided.
1 commit
1 branch
N-Dekker / biovault_bfloat16
Watch 1
Star 0
Fork 1
Code
Issues 0
Pull requests 0
Actions
Projects 0
Wiki
Security
Insights
A bfloat16 implementation for BioVault projects
1 contributor
Apache-2.0
libcg / bfp
Watch 31
Star 218
Fork 21
Code
Issues 2
Pull requests 0
Actions
Projects 0
Wiki
Security
Insights
Beyond Floating Point - Posit C/C++ implementation
posit
gustafson
ieee754
unum
122 commits
stillwater-sc / universal
Watch 19
Unstar 125
Fork 16
Code
Issues 8
Pull requests 0
Actions
Projects 3
Wiki
Security
Insights
MIT
cjdelisle / libposit
Watch 1
Unstar 7
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Code
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Actions
Projects 0
Wiki
Security
Insights
A library for working with the posit number type.
46 commits
1 branch
0 packages
0 releases
1 contributor
View license
Branch: master
New pull request
Create new file
Upload files
Find file
Clone or download

https://github.com/cjdelisle/libposit

Types

libposit defines the following types:

- `posit8_t` 8 bit posit
  - `posit8x2_t` pair of 8 bit posits, result of `*_exact` functions.
- `posit16_t` 16 bit posit
  - `posit16x2_t` pair of 16 bit posits, result of `*_exact` functions.
- `posit32_t` 32 bit posit
  - `posit32x2_t` pair of 32 bit posits, result of `*_exact` functions.
- `posit64_t` 64 bit posit
  - `posit64x2_t` pair of 64 bit posits, result of `*_exact` functions.
- `posit128_t` 128 bit posit, result of posit64 `*_promote` functions. Only functions which work on a `posit128_t` are `posit128_iexp()` and `posit128_fract()`.

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- `posit16_t` 1
  - `posit16`
- `posit32_t` 3
  - `posit32`
- `posit64_t` 6
  - `posit64`
- `posit128_t`

  `posit128_ie`

Operations

For each of these types, libposit provides the following functions:

- `posit<X>_t posit<X>_add(posit<X>_t x, posit<X>_t y)` : Add two posits together, output a rounded result.
- `posit<X>_t posit<X>_sub(posit<X>_t x, posit<X>_t y)` : Subtract one posit from another, output a rounded result.
- `posit<X>x2_t posit<X>_add_exact(posit<X>_t x, posit<X>_t y)` : Output 2 results, `sum` and `remainder` which when added will result in the exact same value as the inputs `x` and `y` but where the absolute value of `remainder` is as small as possible.
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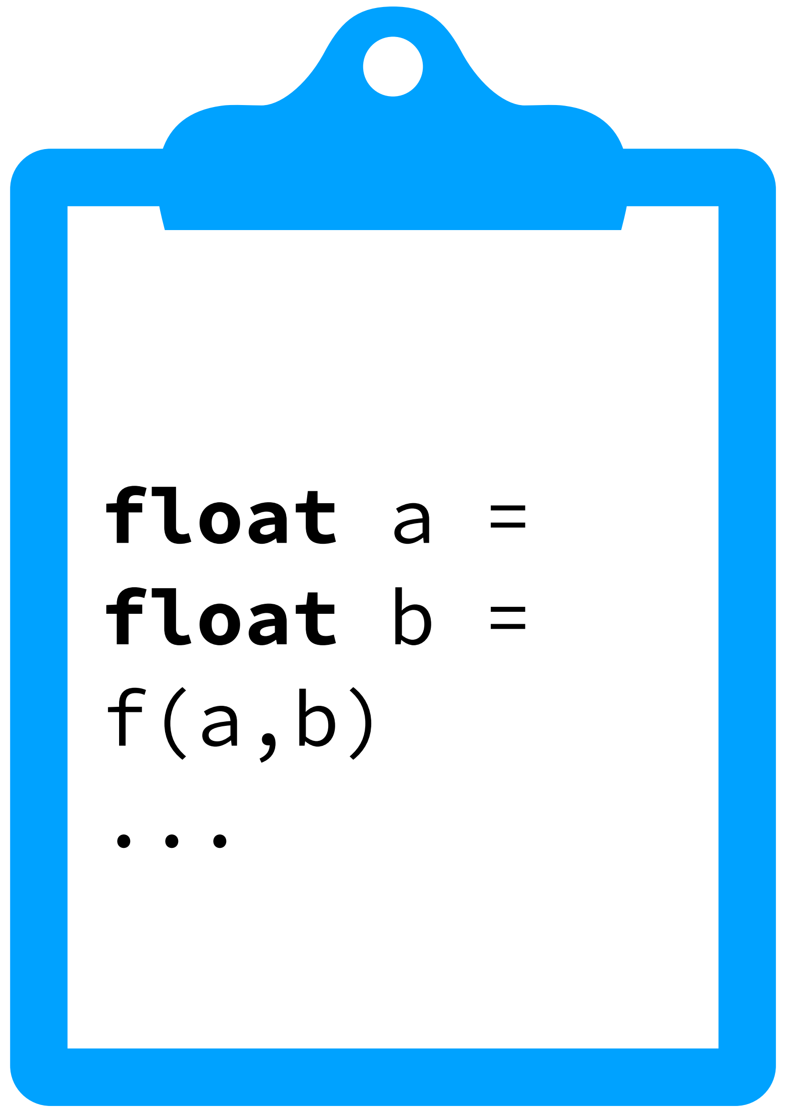
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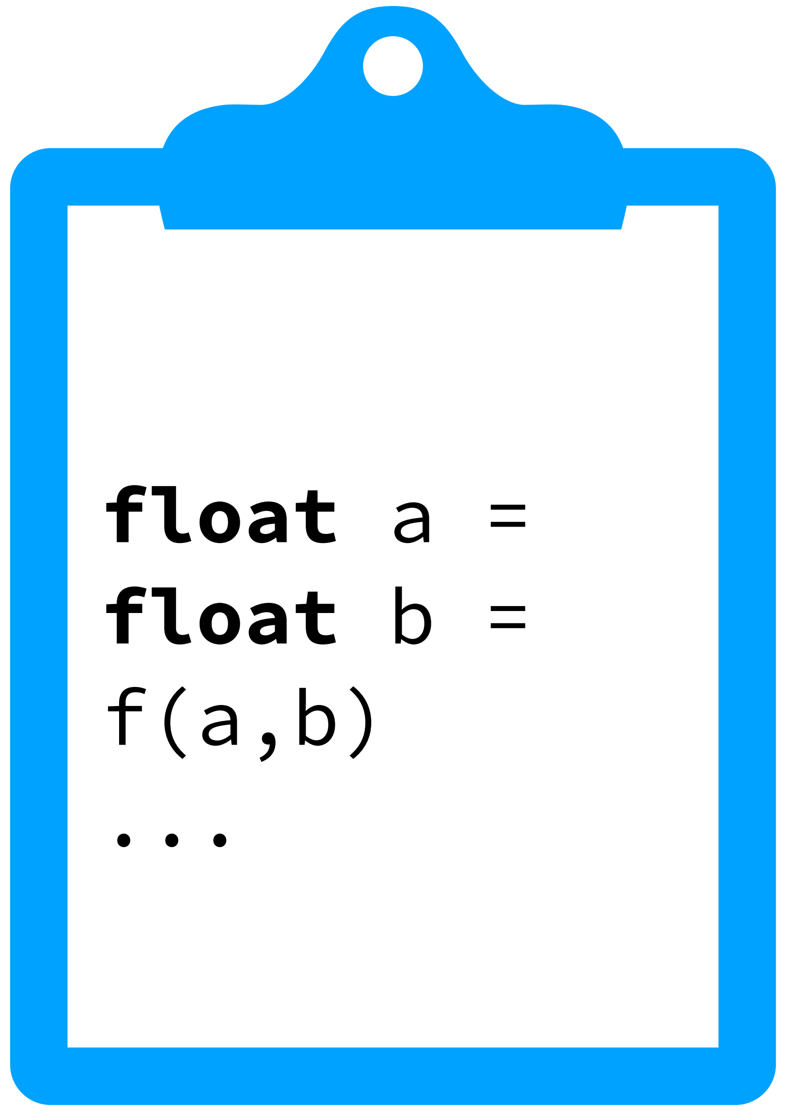
float b =
f(a,b)
...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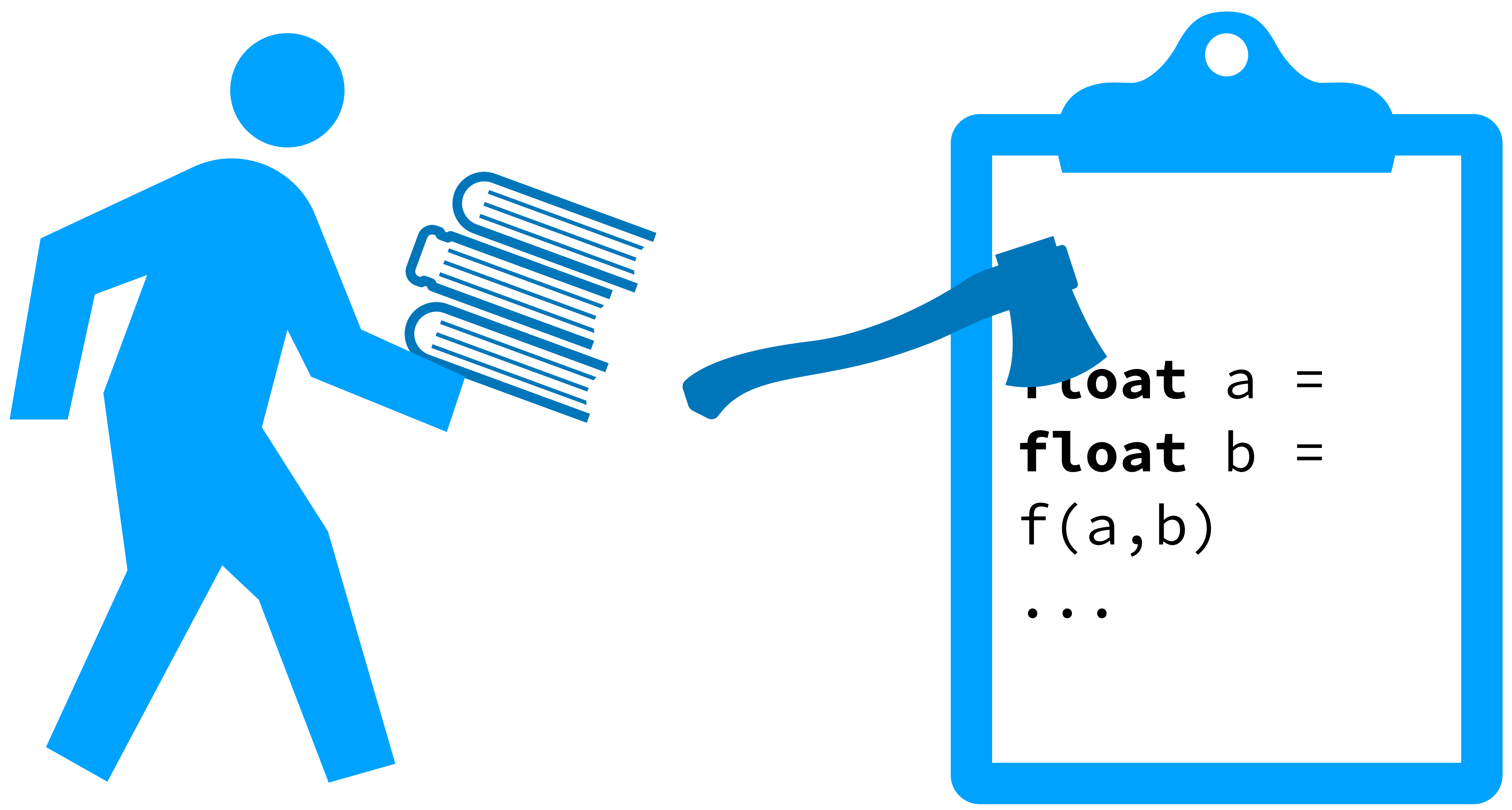
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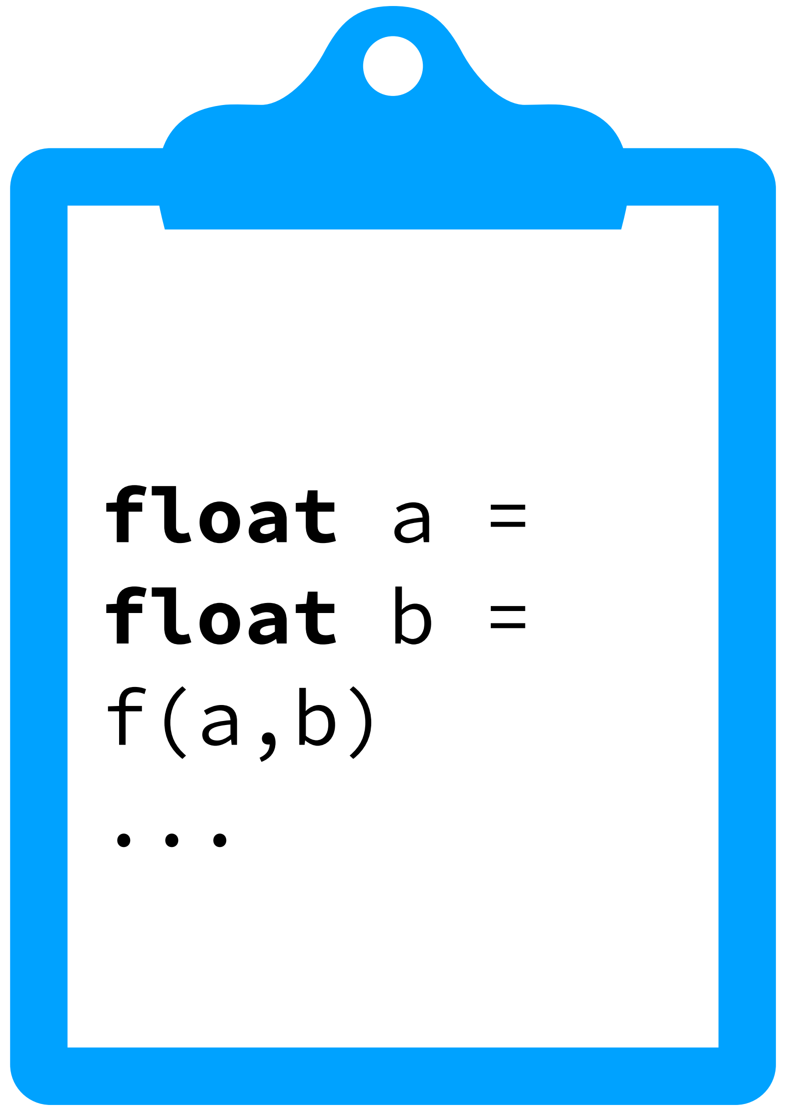
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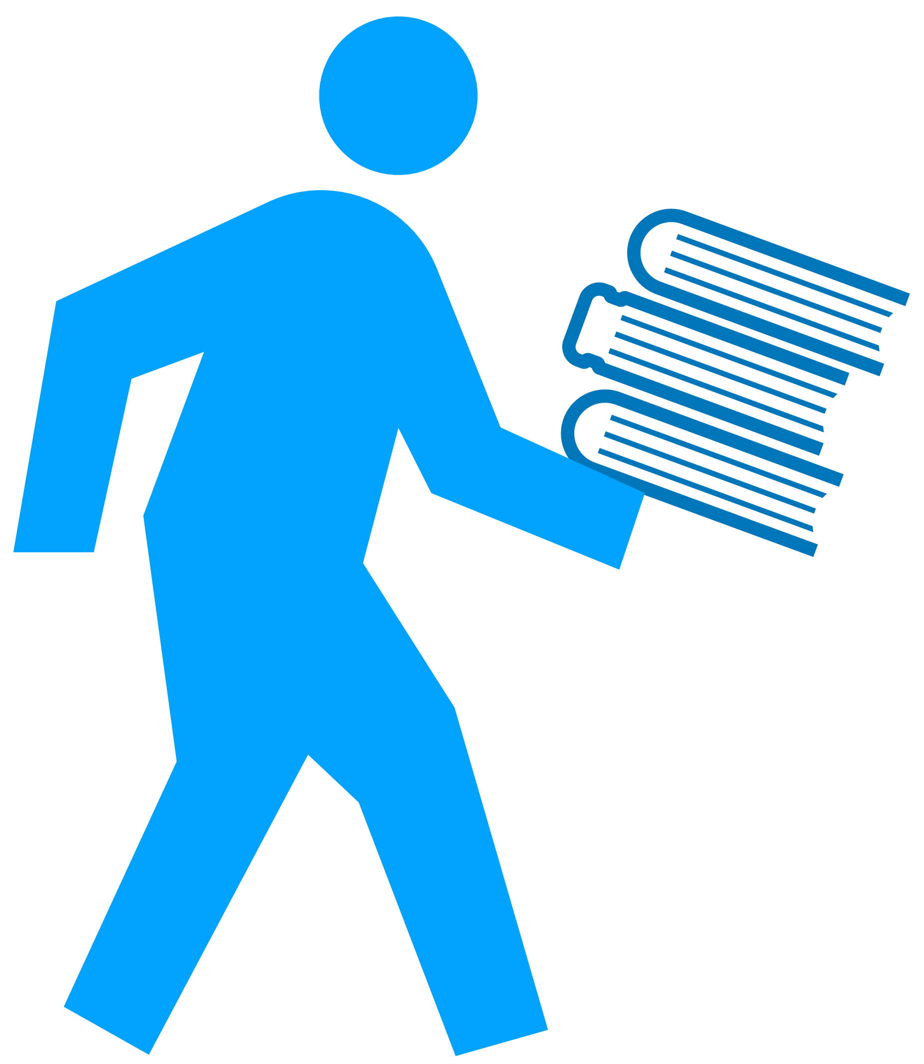

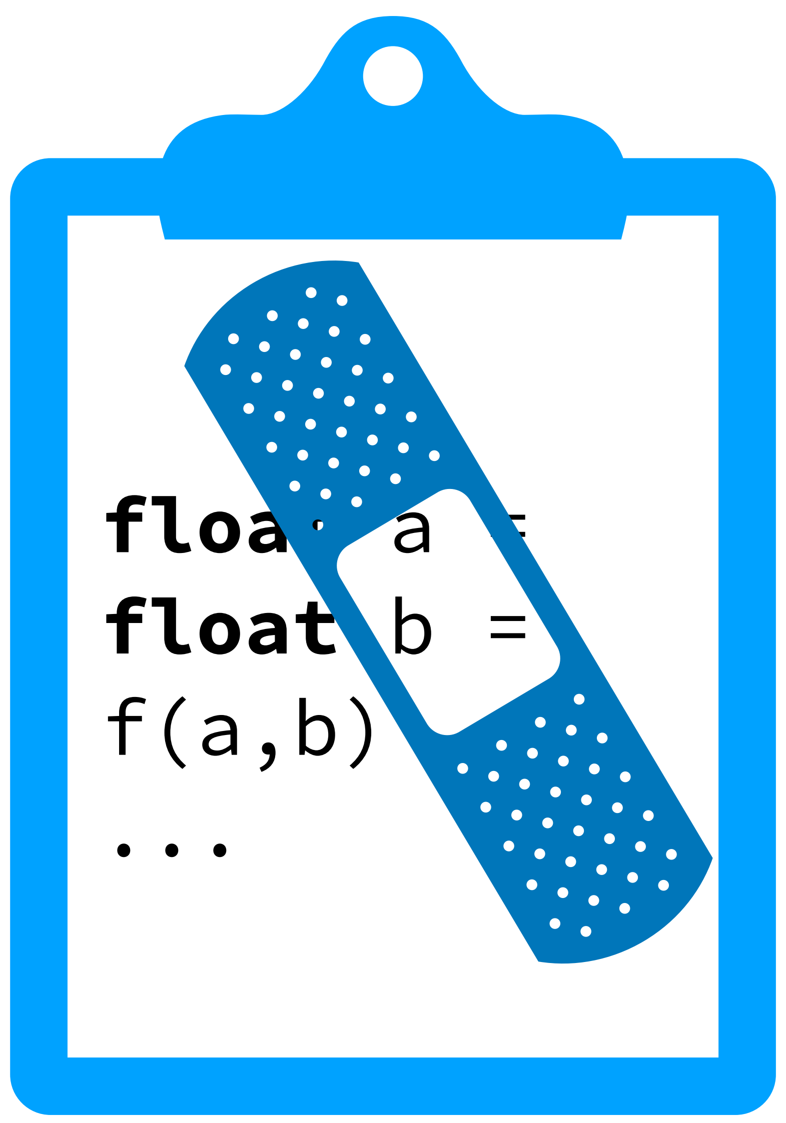
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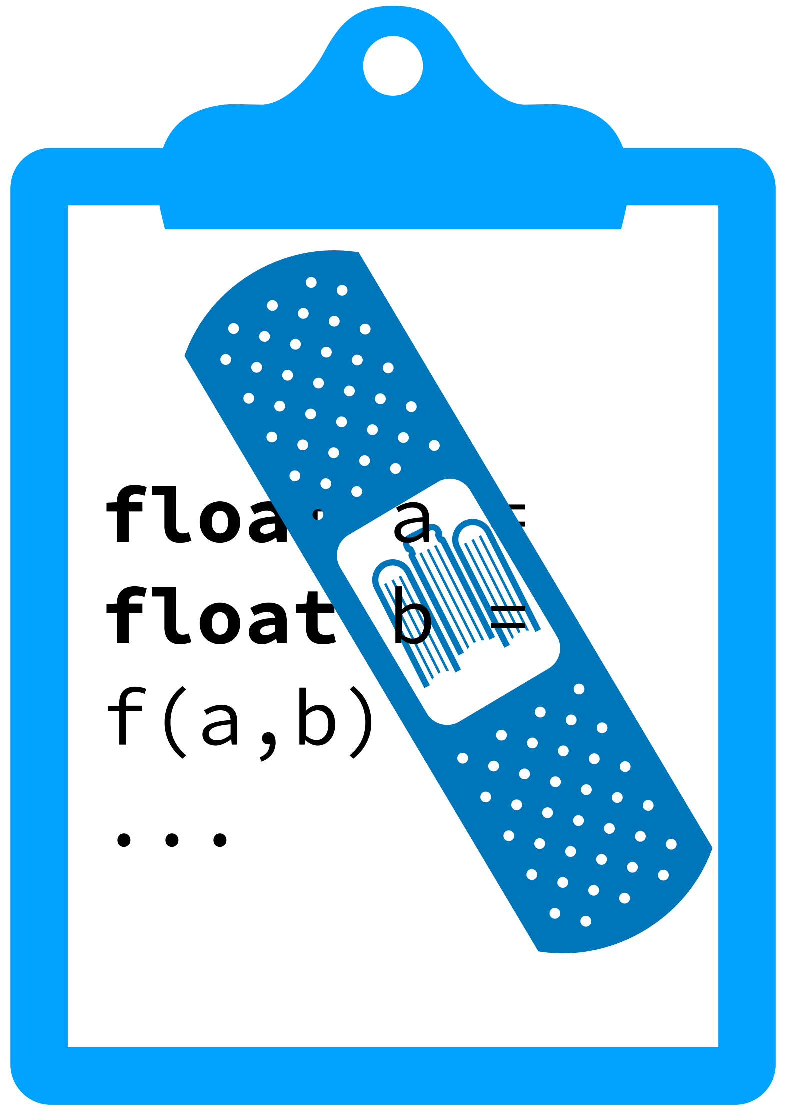
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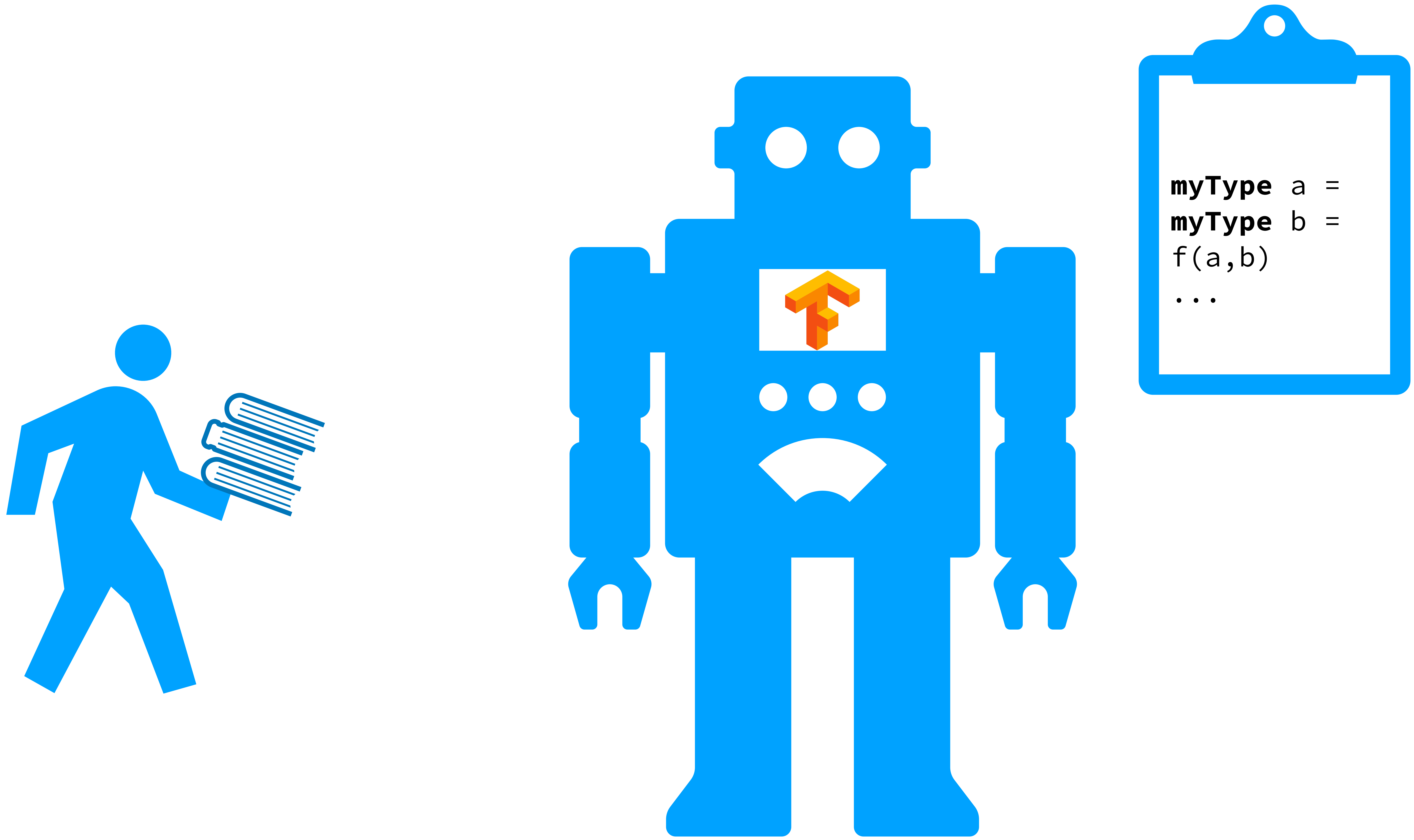
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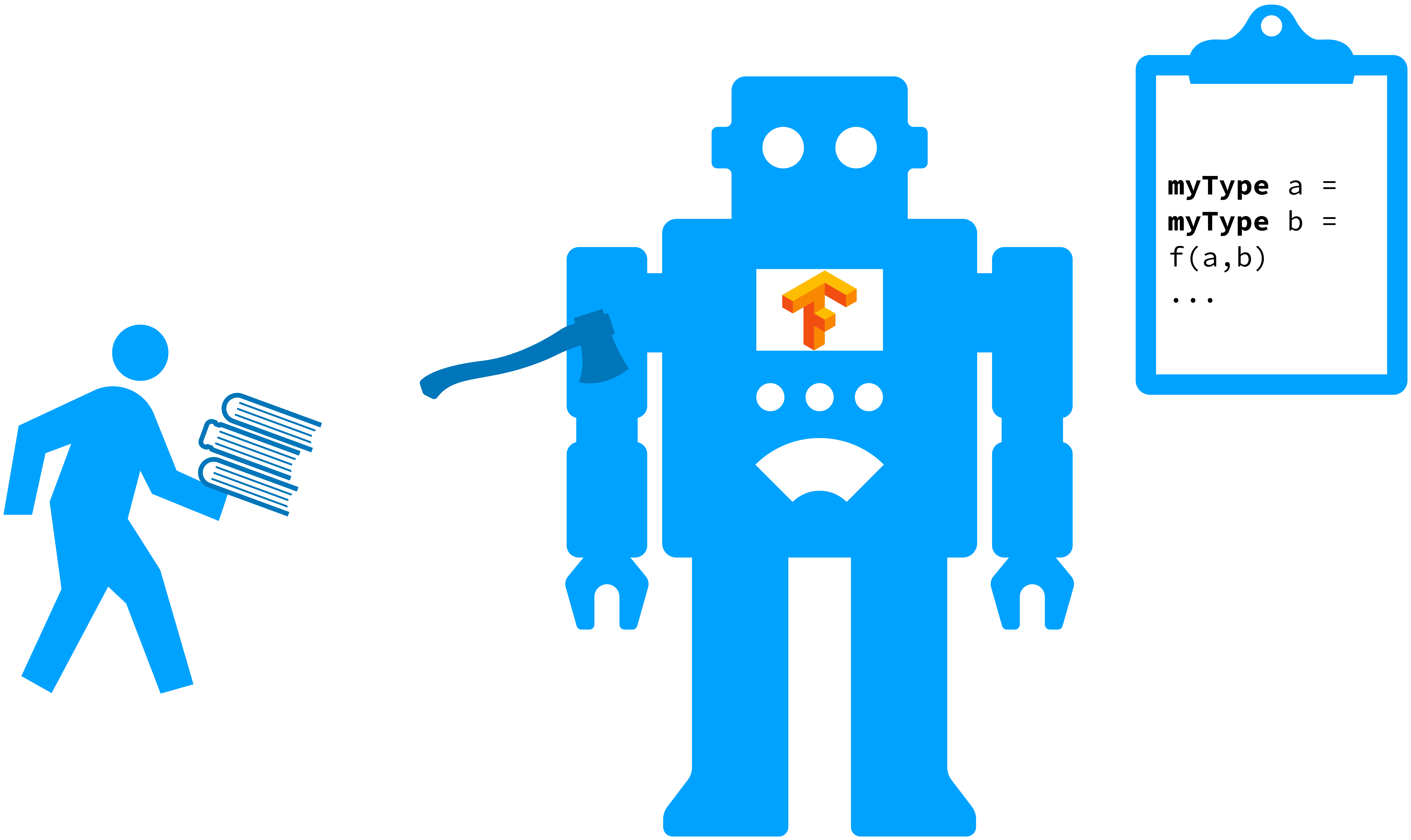
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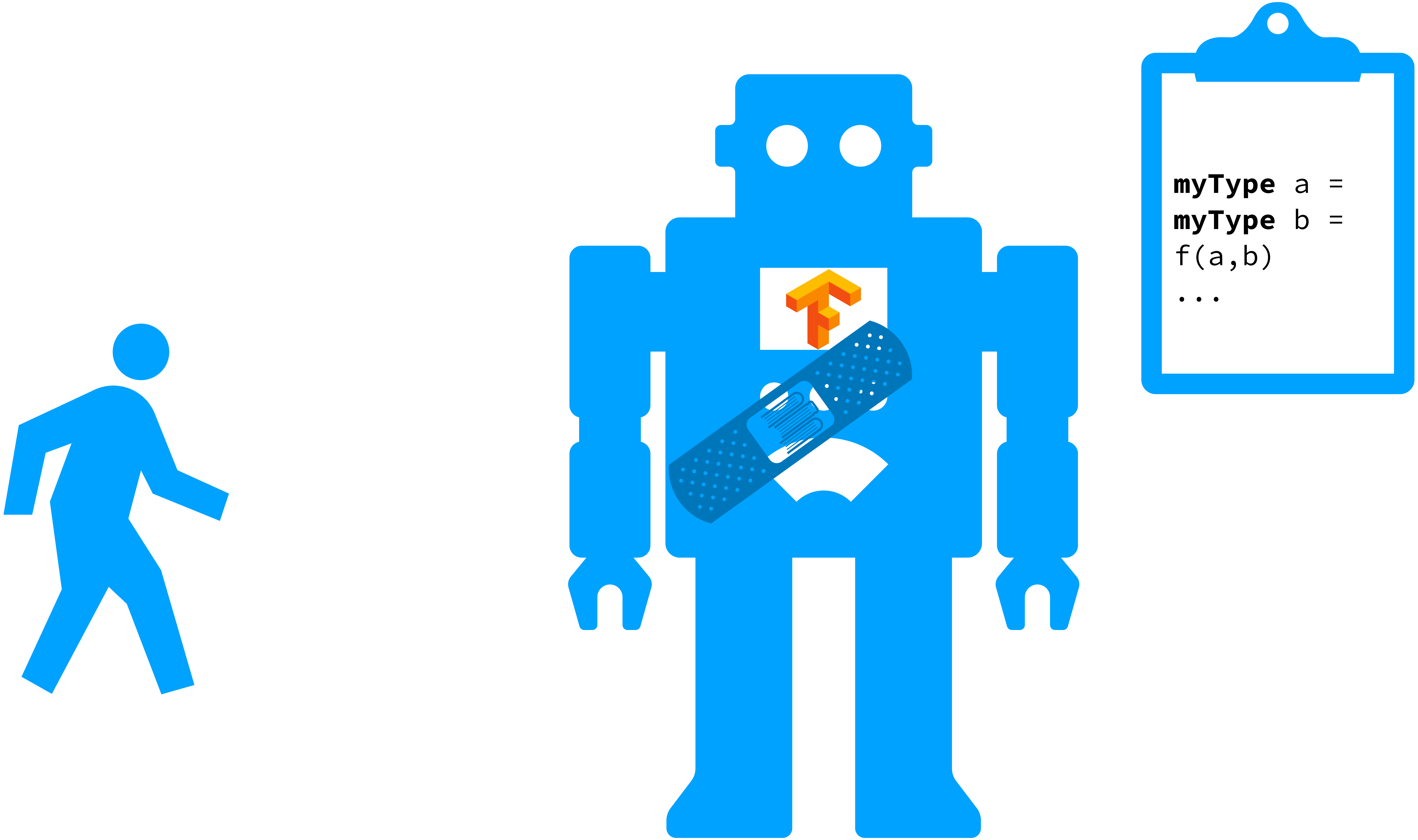
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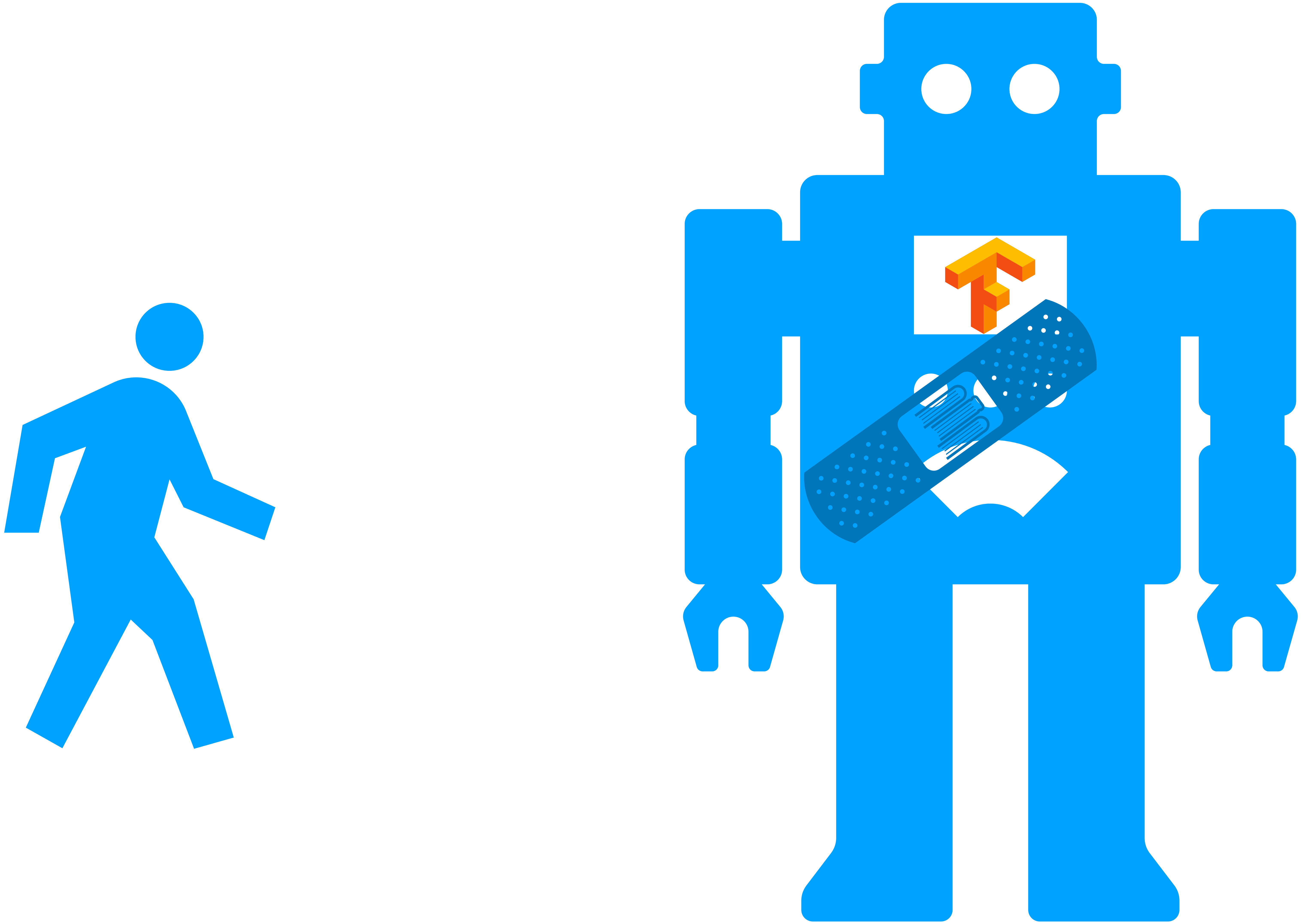

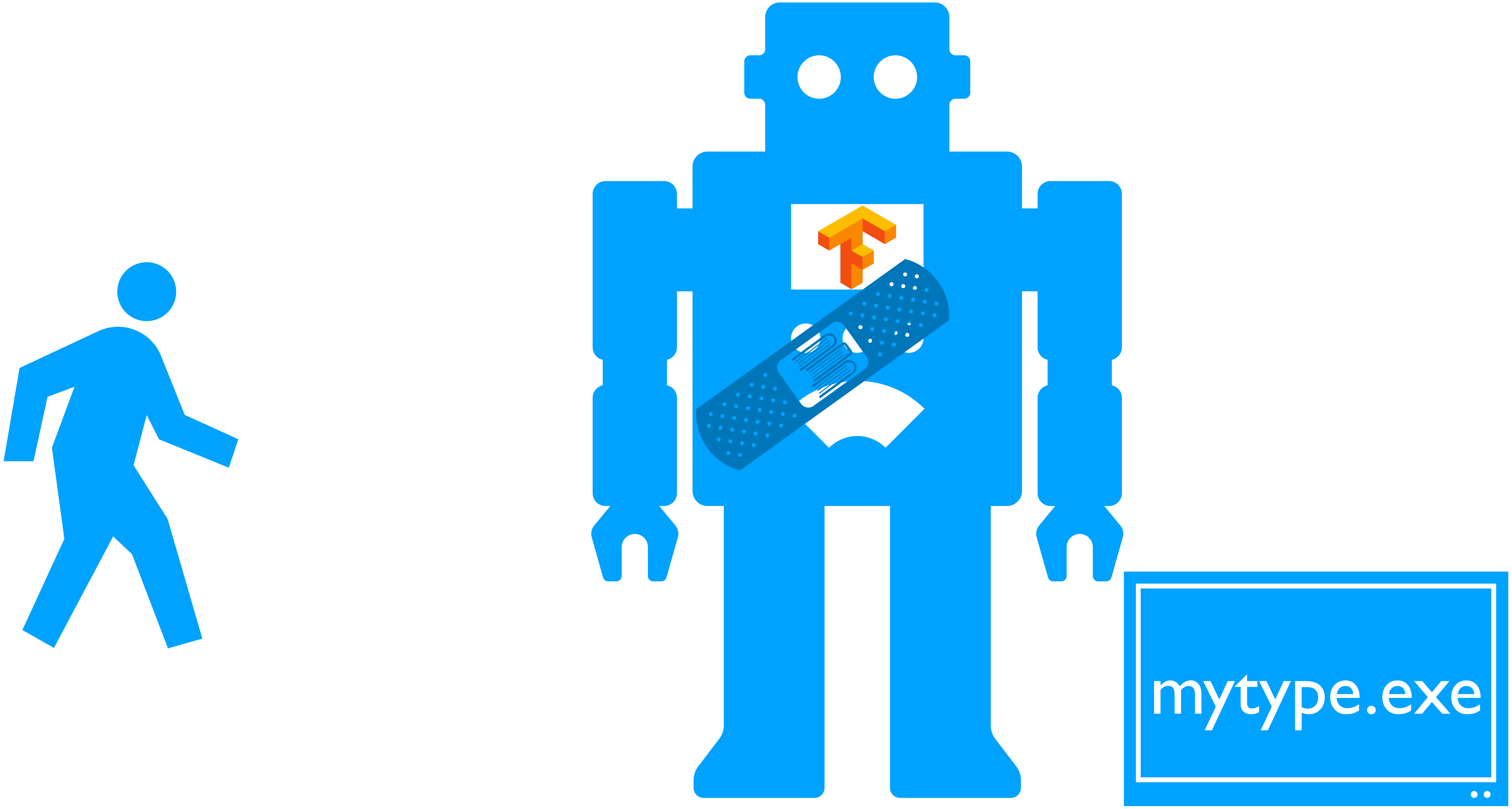
mytype.exe

An Example in the Wild!

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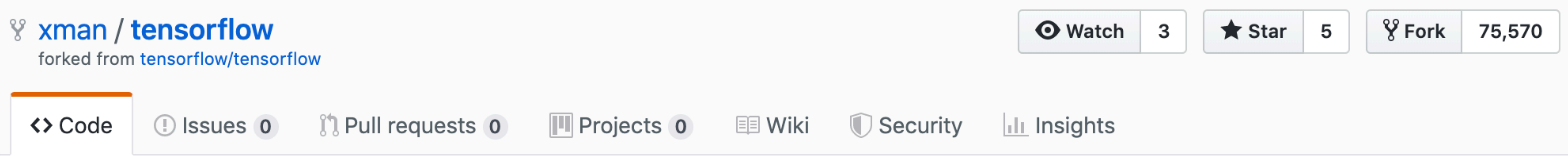

https://github.com/xman/tensorflow/tree/posit

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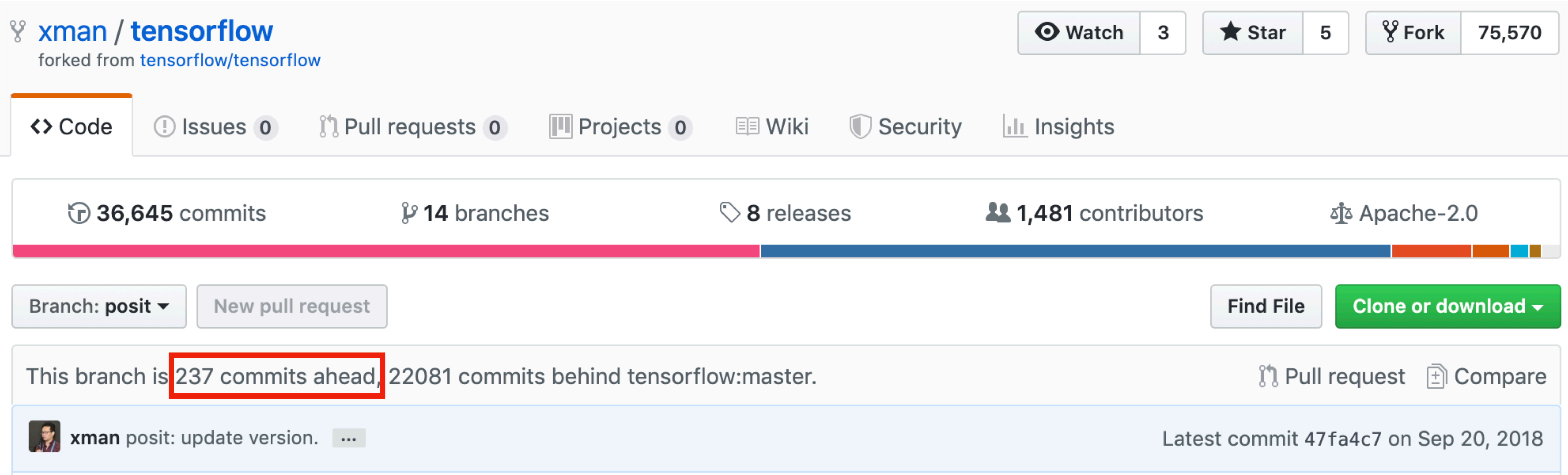

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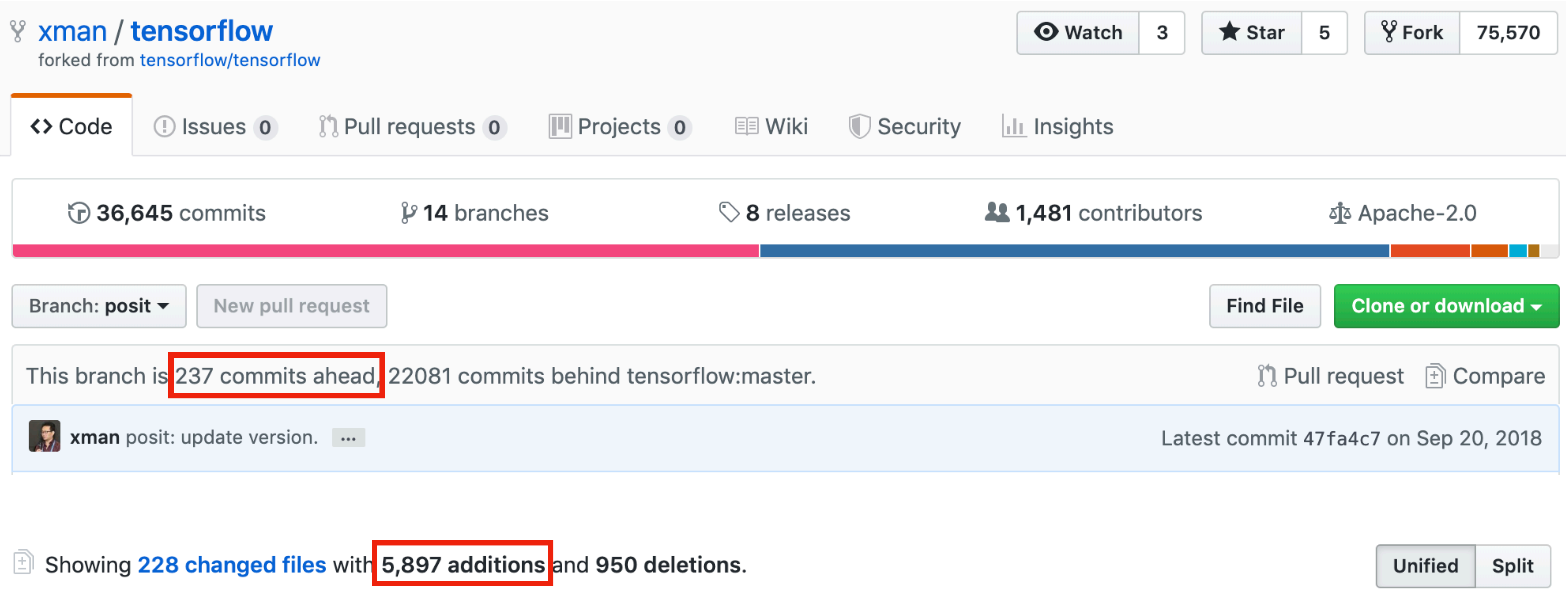

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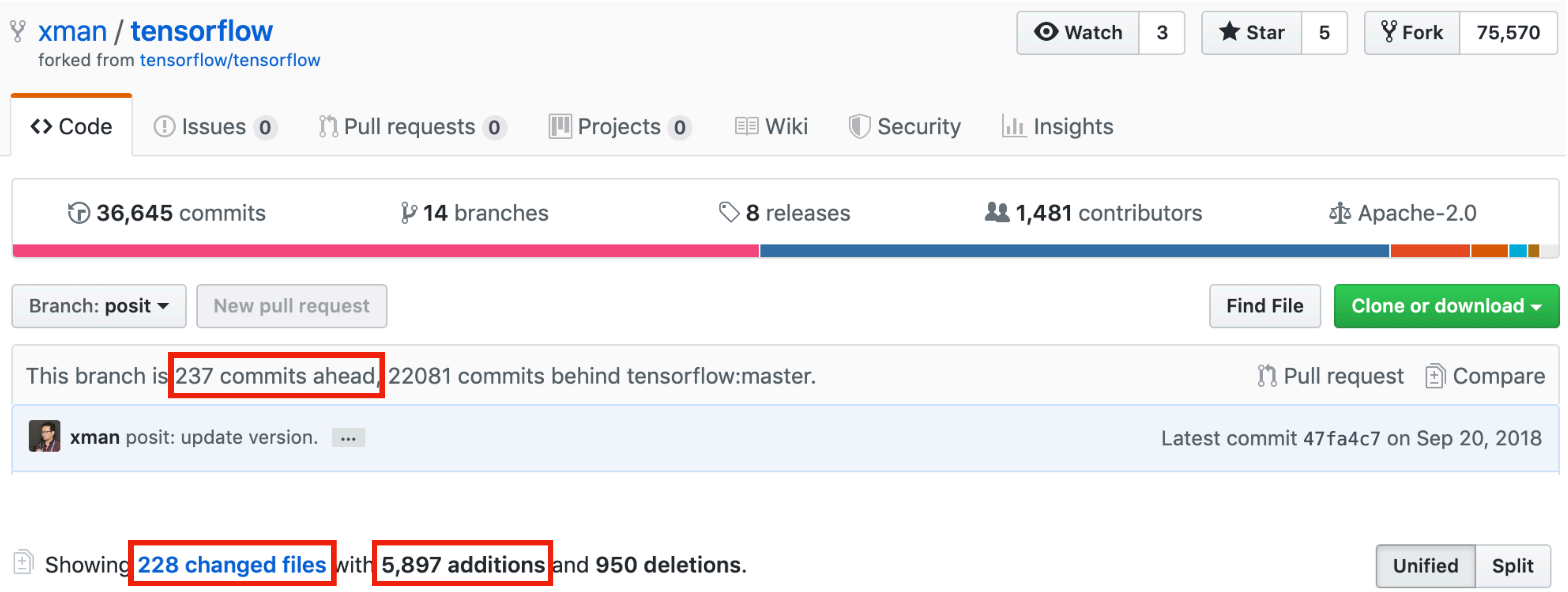

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The computational demands of deep learning require new datatypes…

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…but datatype research is difficult!

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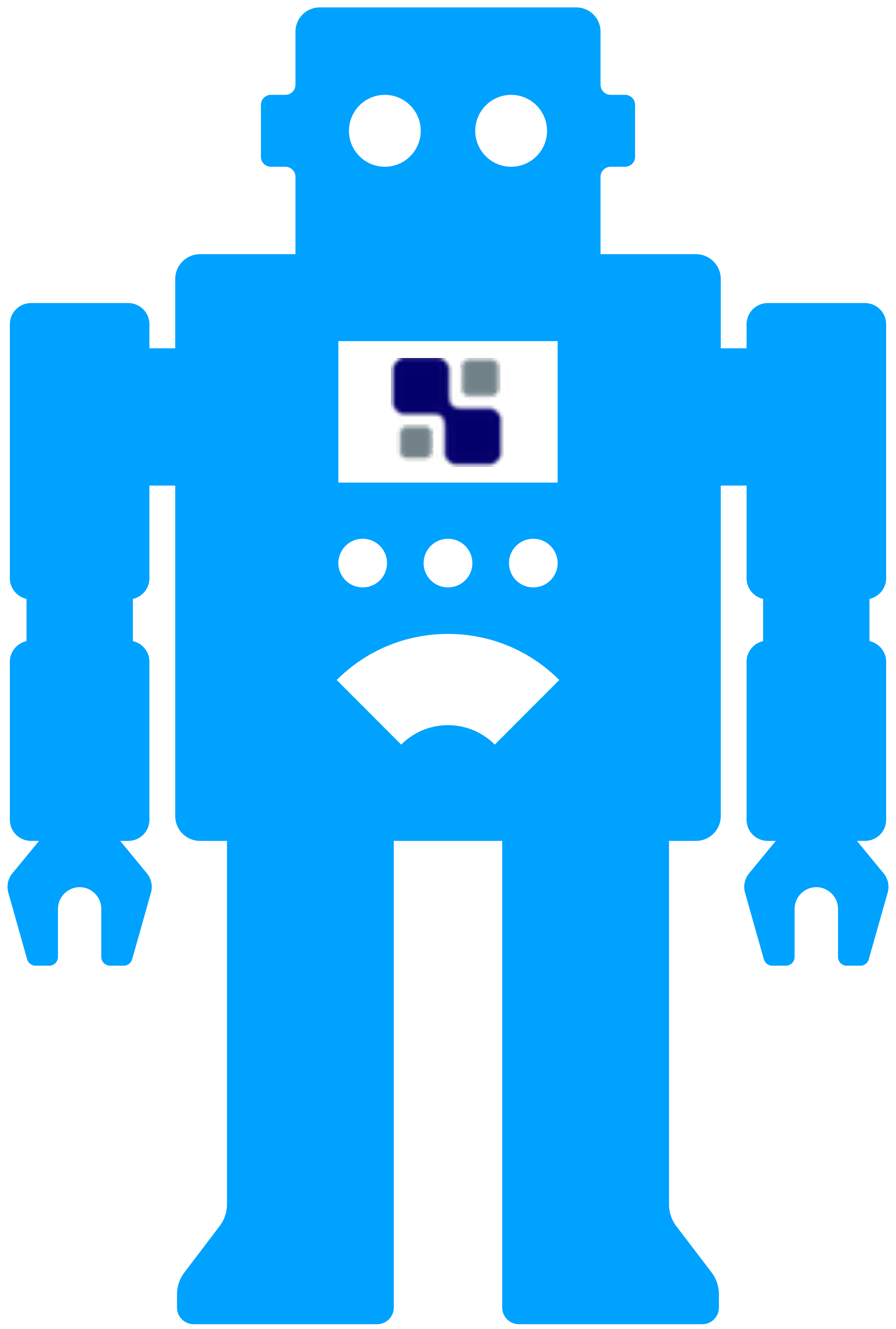
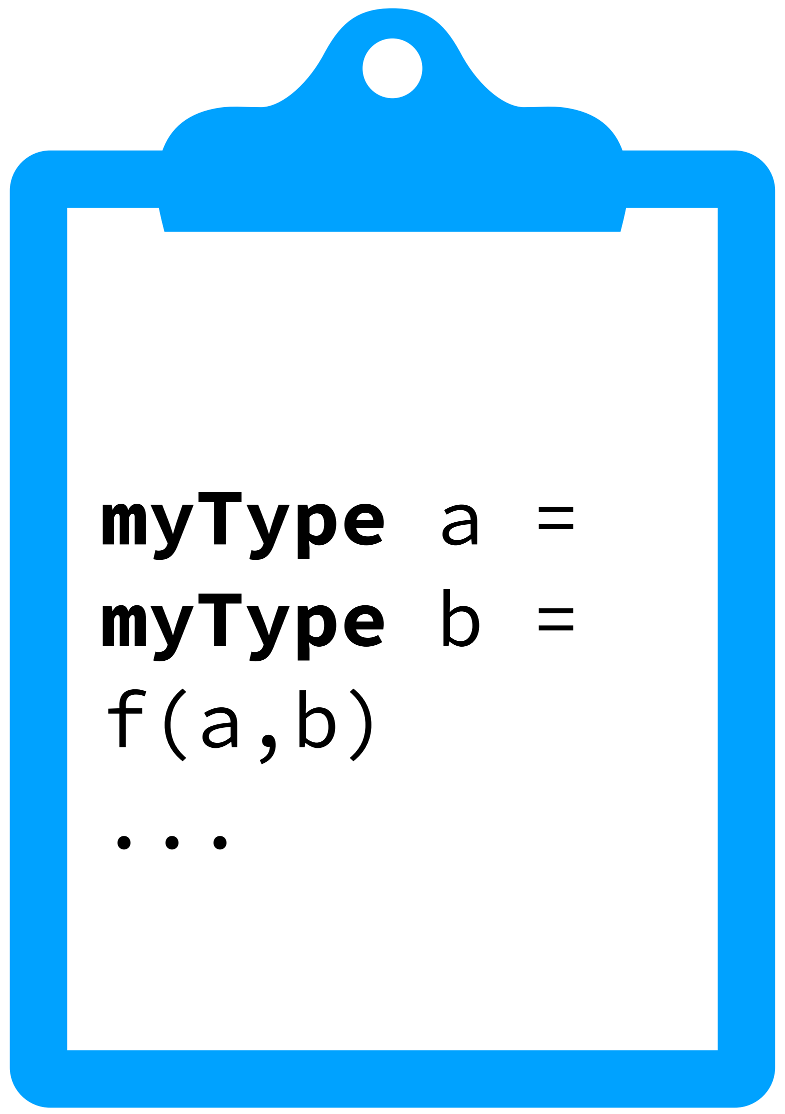
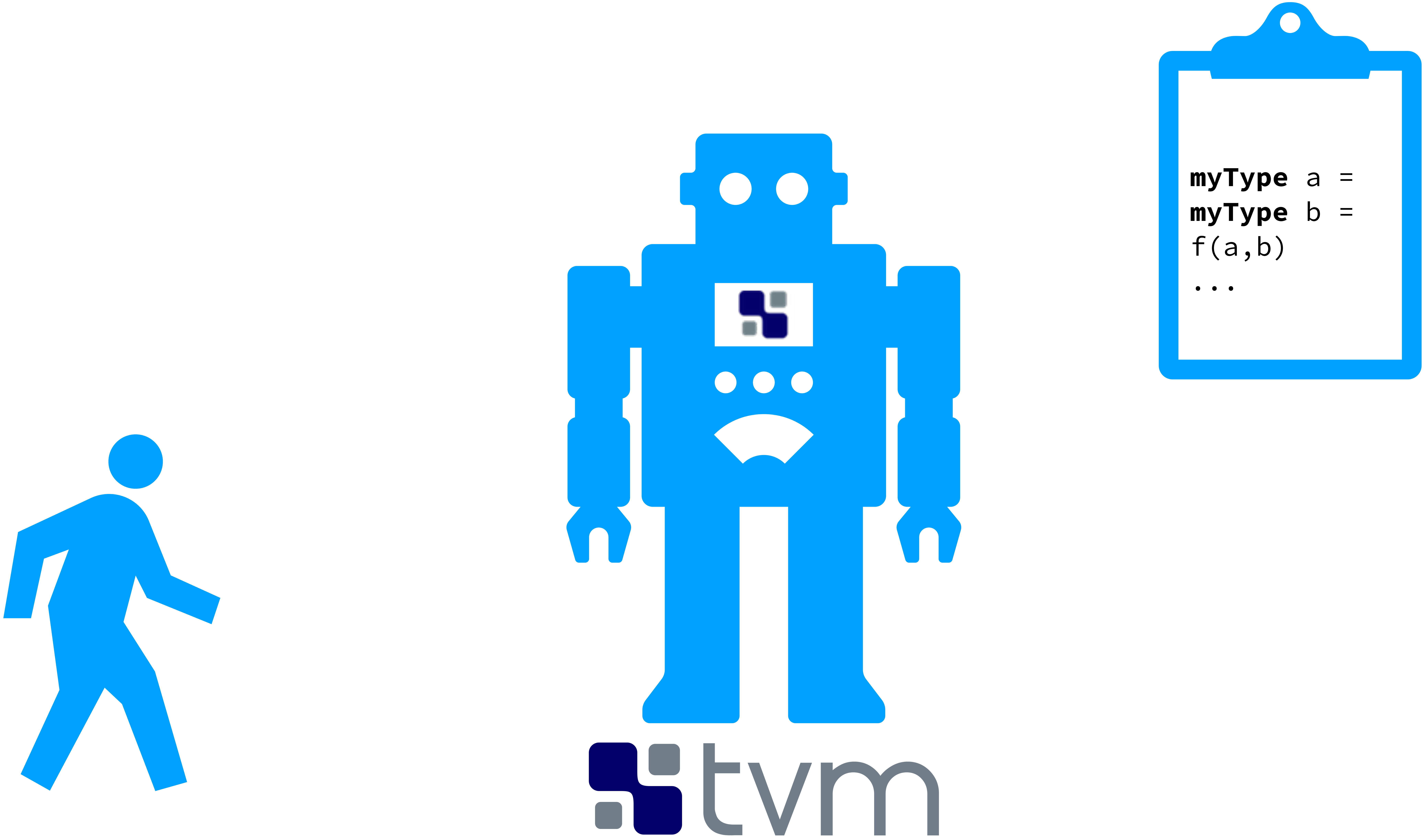
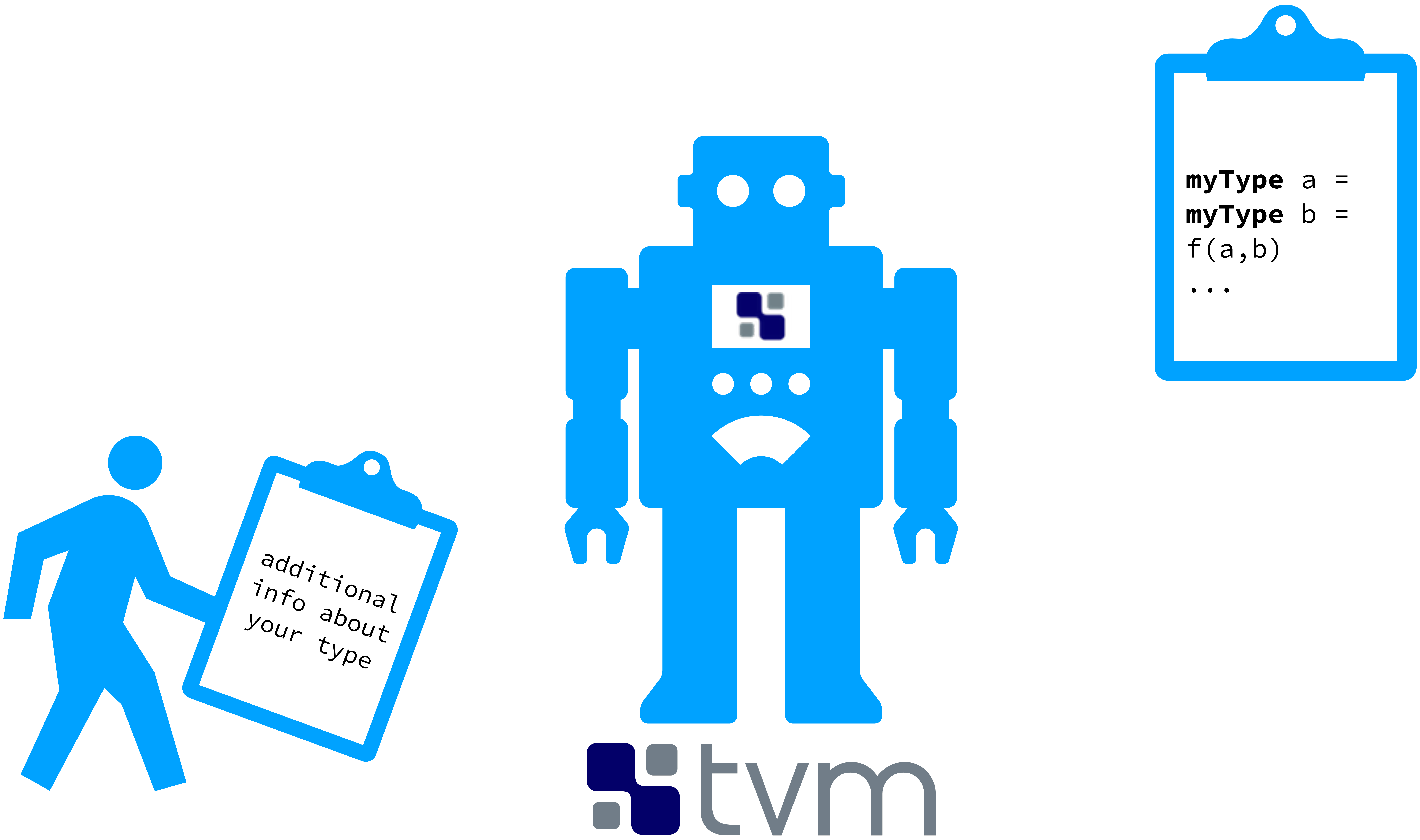
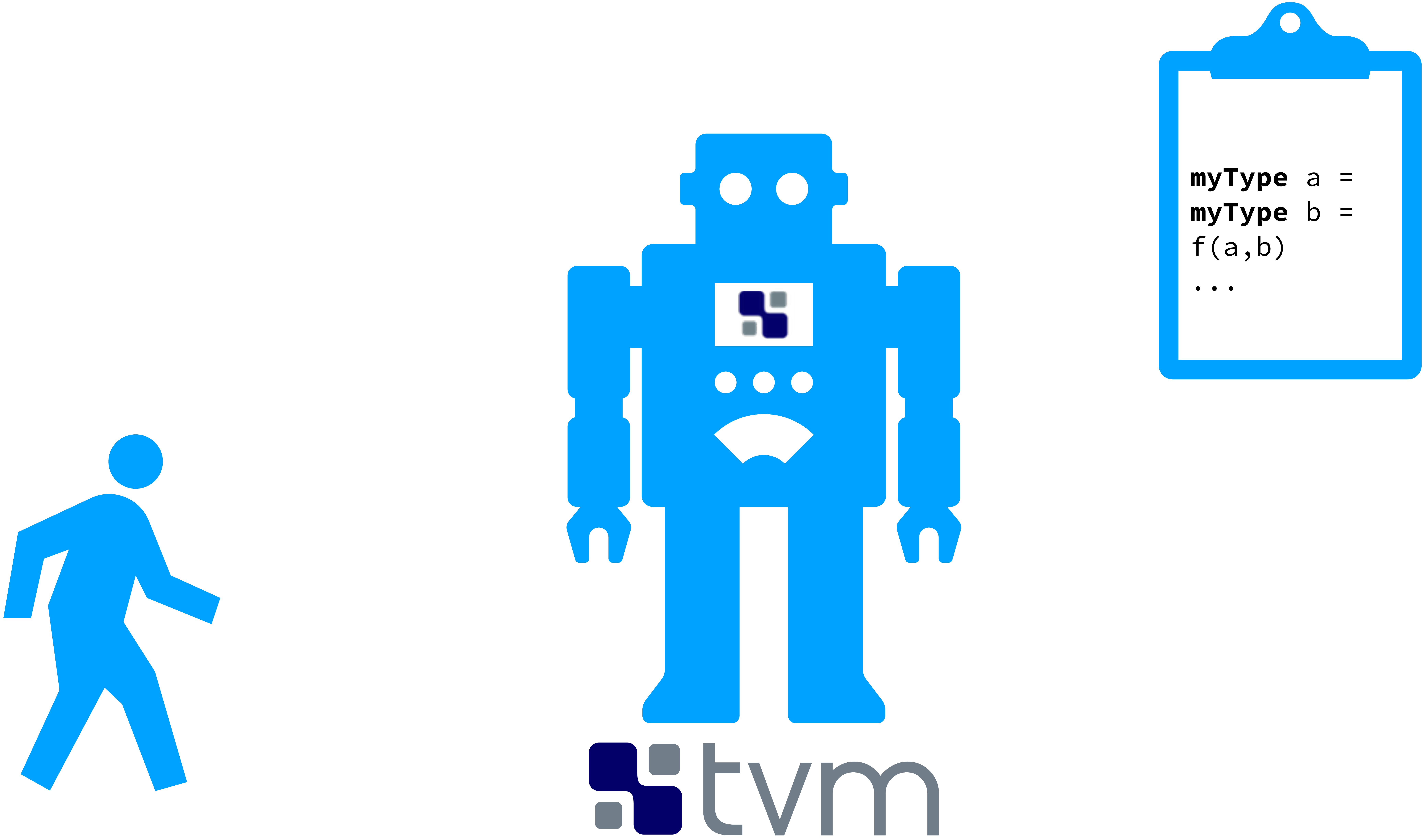
Our solution: the Bring Your Own Datatypes framework.




myType a =
myType b =
f(a,b)
...


myType a =
myType b =
f(a,b)
...
tvm


additional info about your type
myType a =
myType b =
f(a,b)
...
tvm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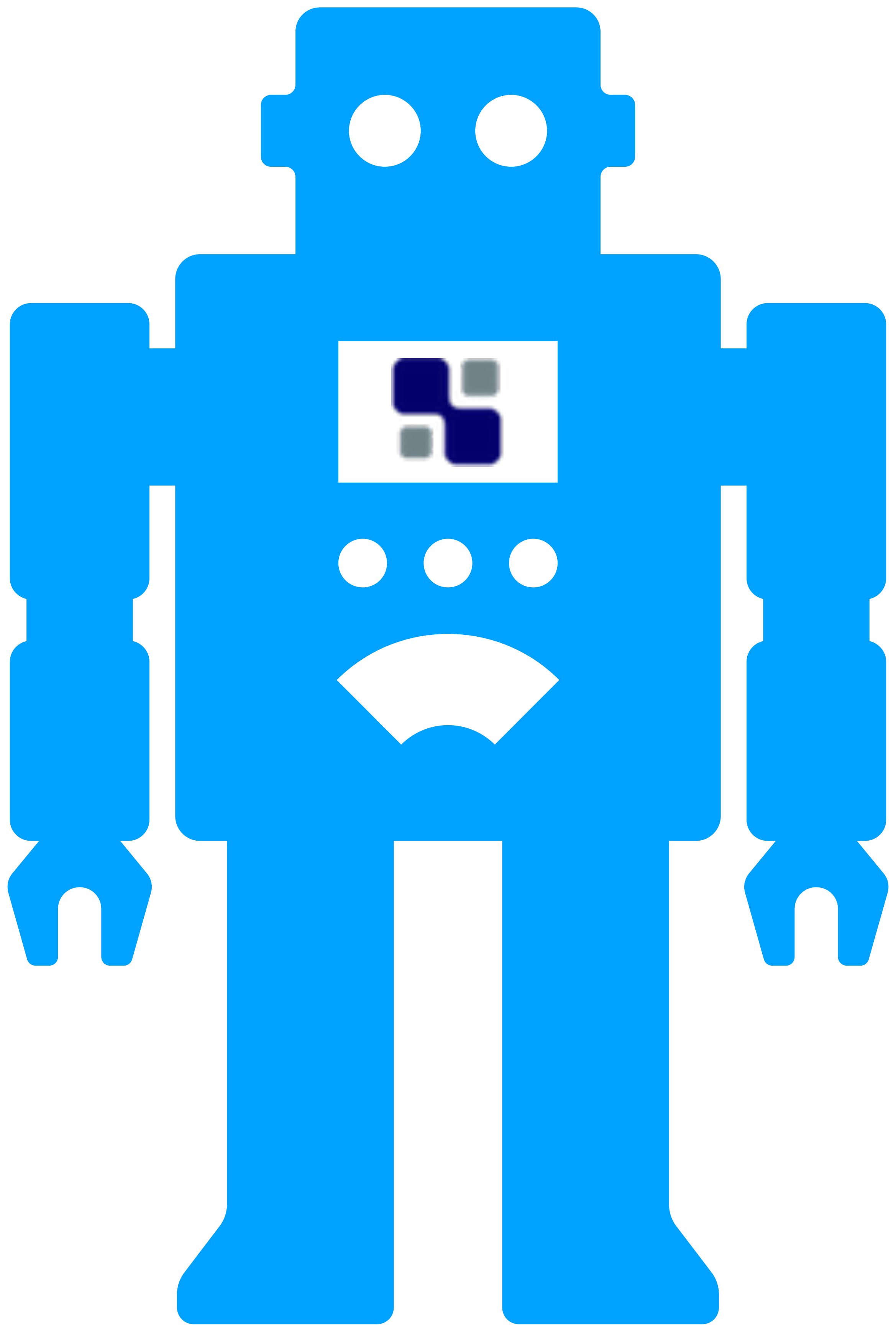

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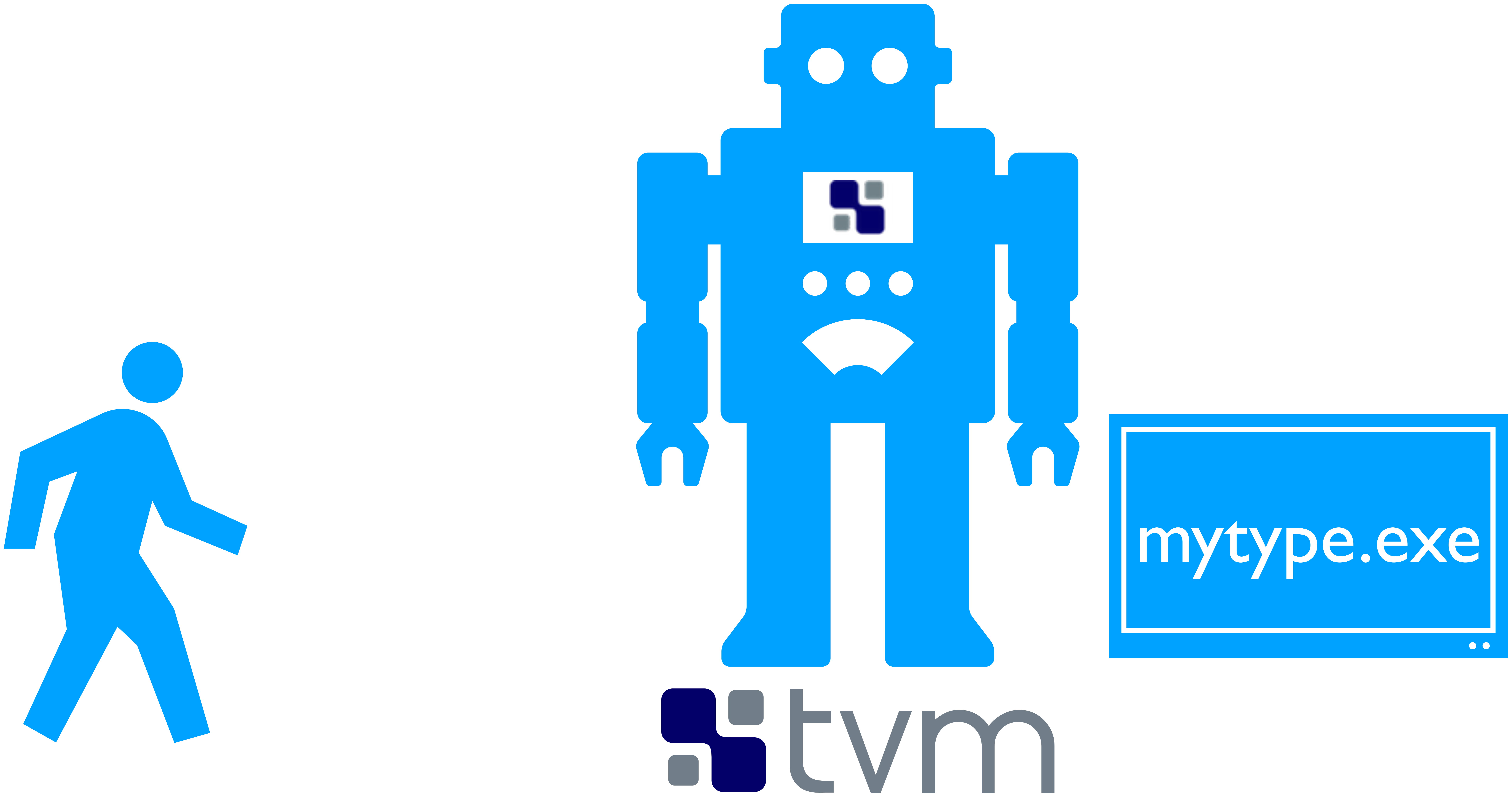
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Bring Your Own Datatypes

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3. TVM **compiles and runs programs** which use the custom datatype, handling the custom datatype by calling into the provided library

But first…what is TVM?

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tvm

An **extensible, optimizing compiler** for deep learning.

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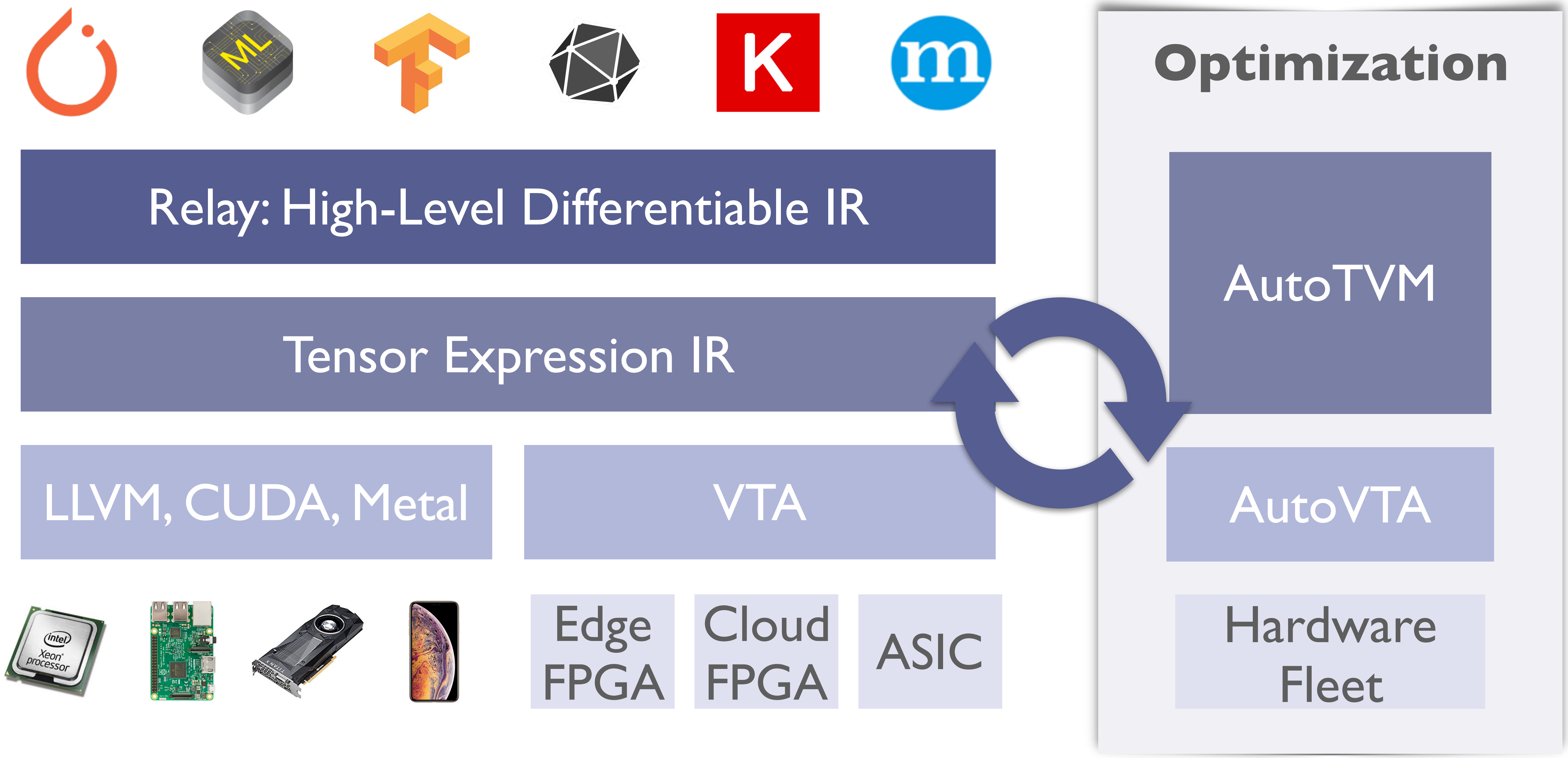
See tvm.ai for more info!

The TVM Stack

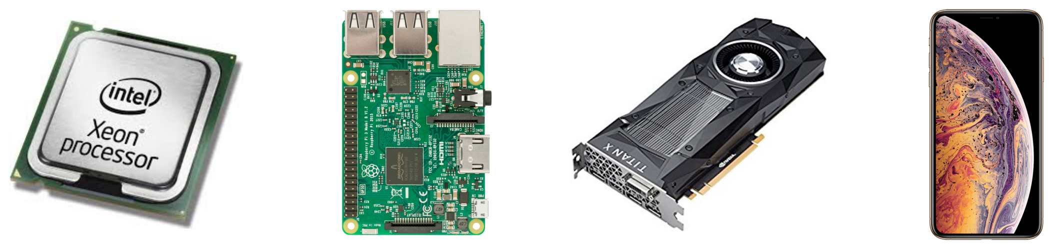


The TVM Stack

TVM IR

LLVM, CUDA, Metal

VTA

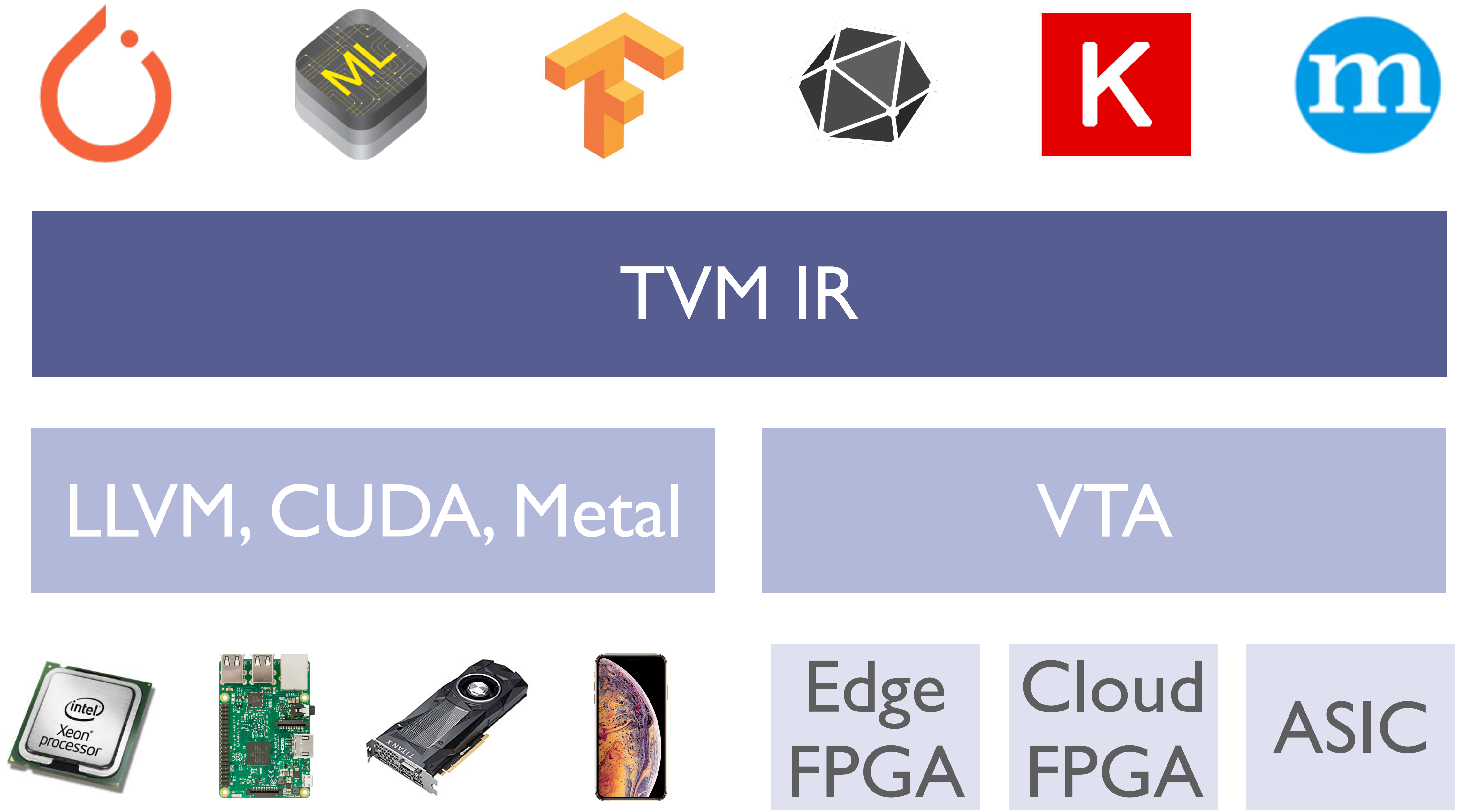


Edge FPGA

Cloud FPGA

ASIC

Datatypes Registry



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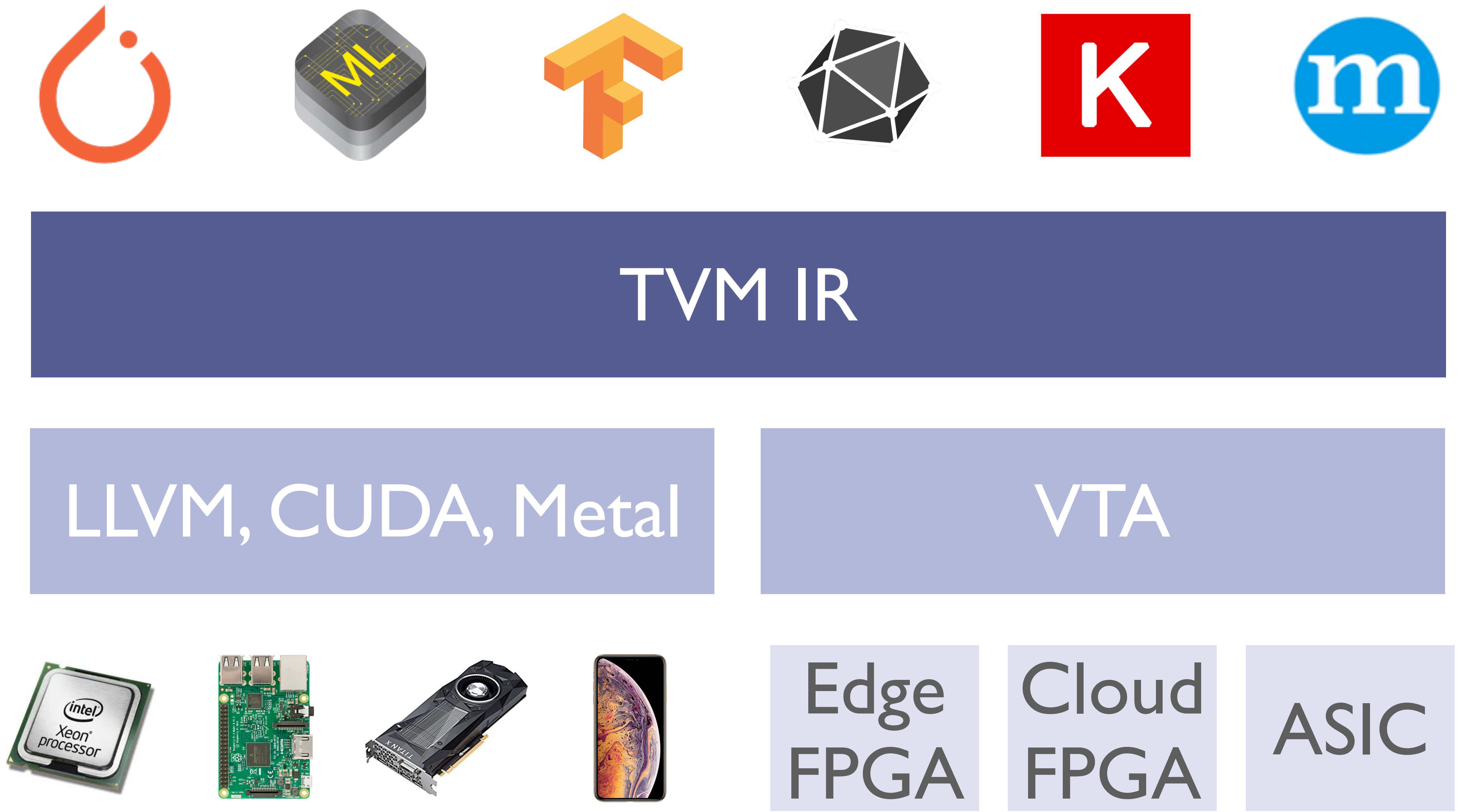

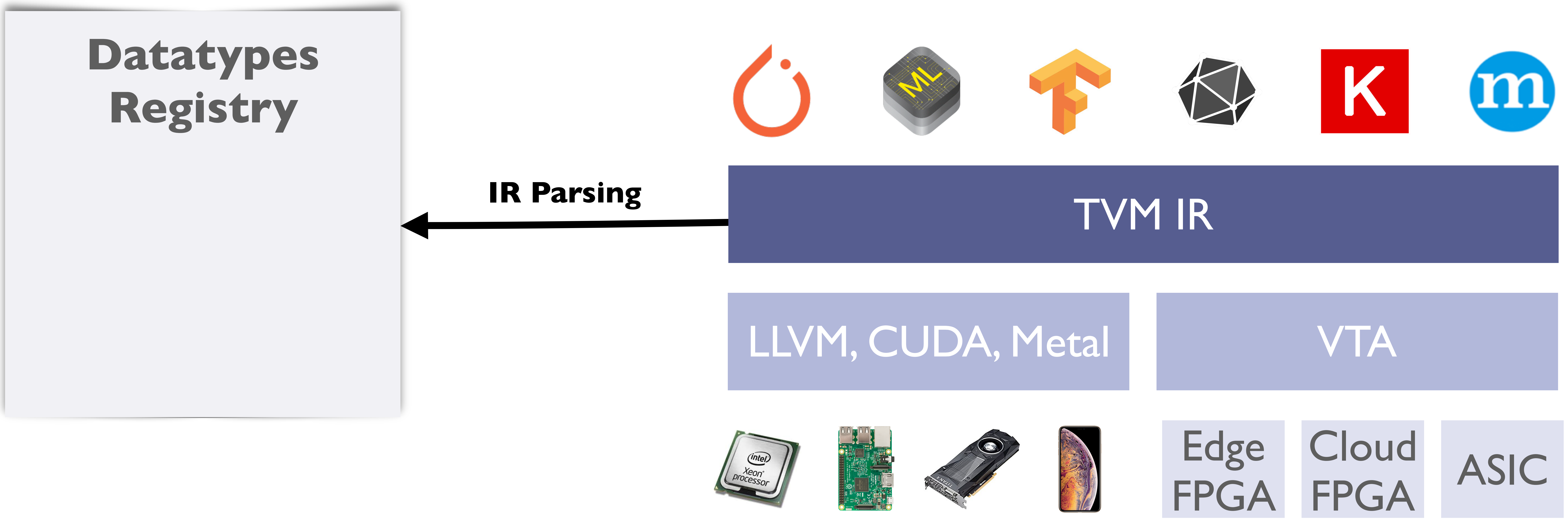
Datatypes Registry
IR Parsing
TVM IR
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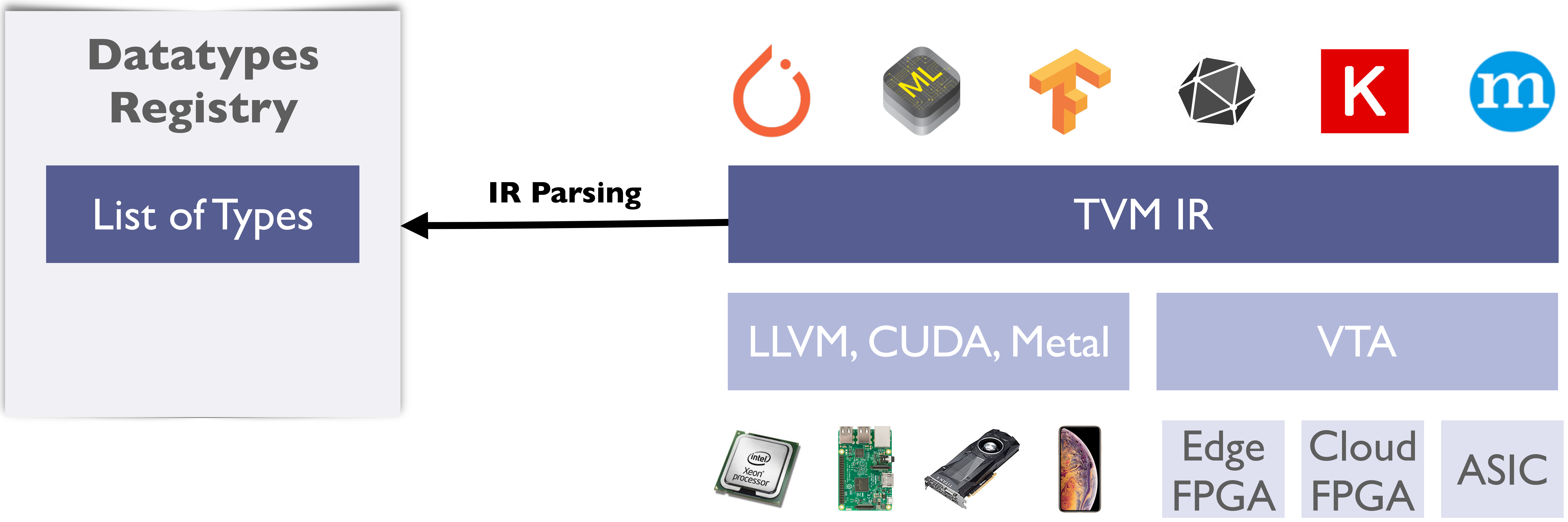
Datatypes Registry
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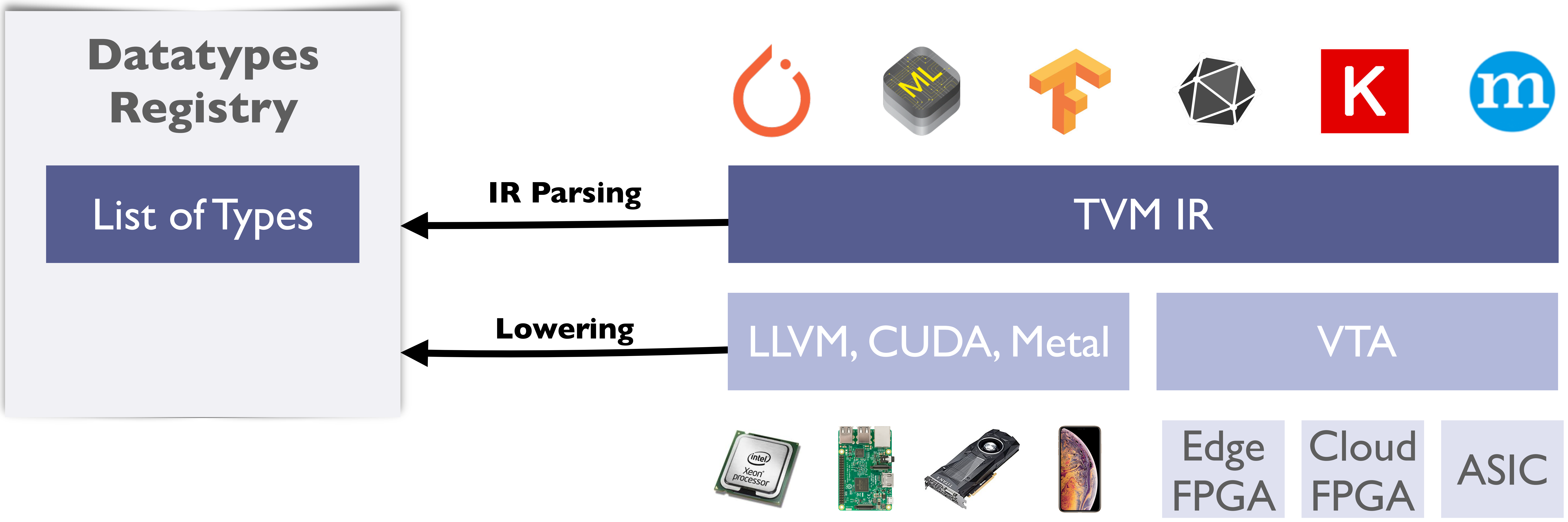
Datatypes Registry
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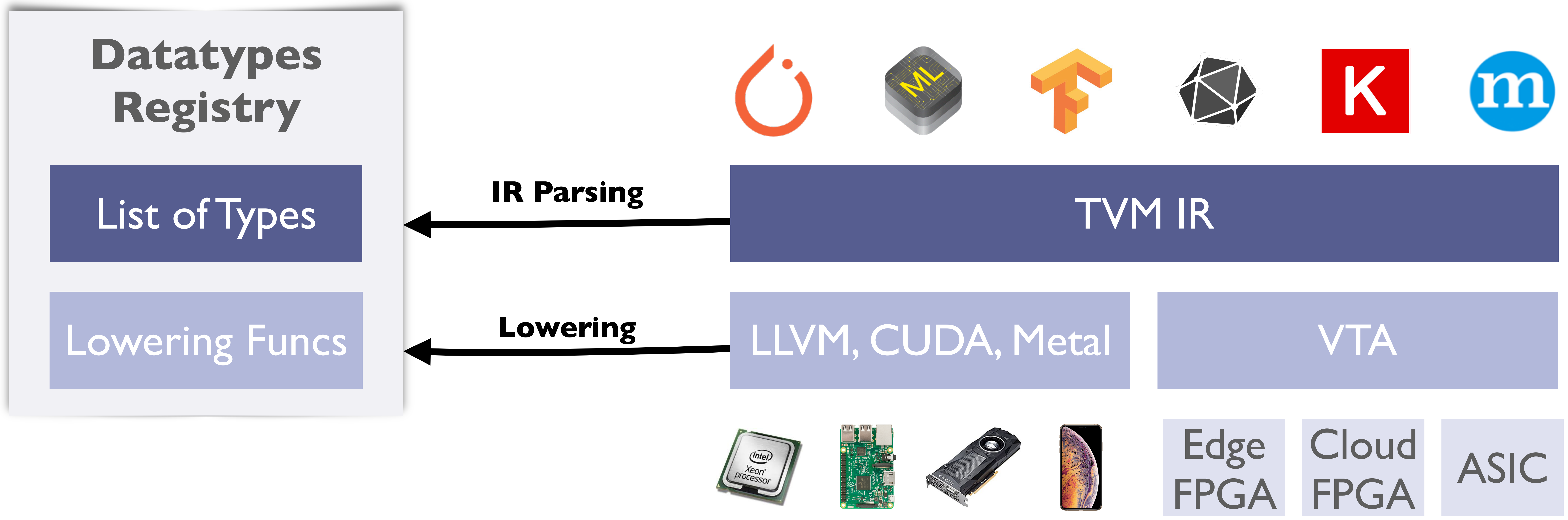
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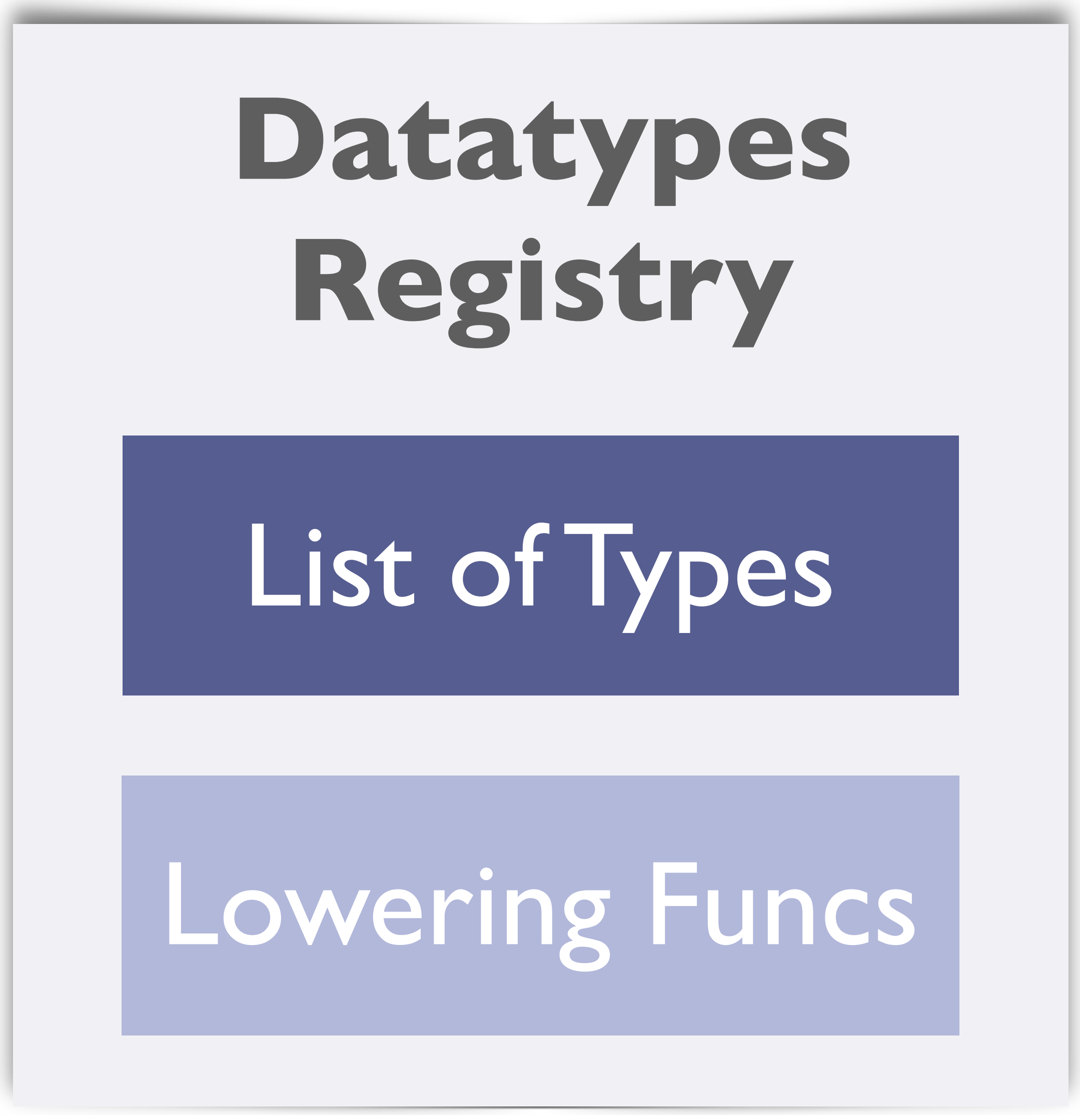
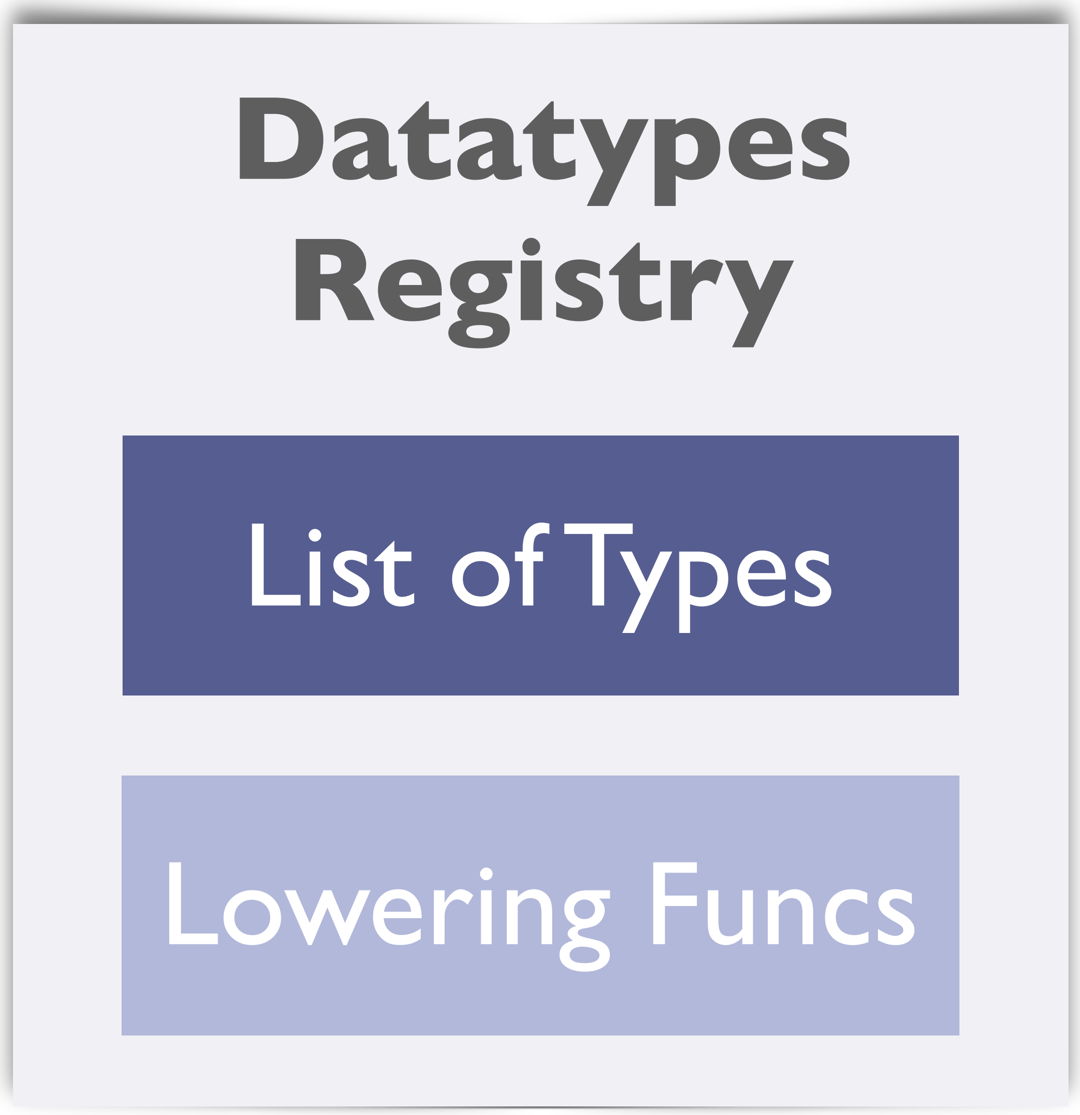
Datatypes Registry

List of Types

Lowering Funcs



To register their datatype, the user provides a name and type code:



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tvm.datatype.register("bfloat", 129)
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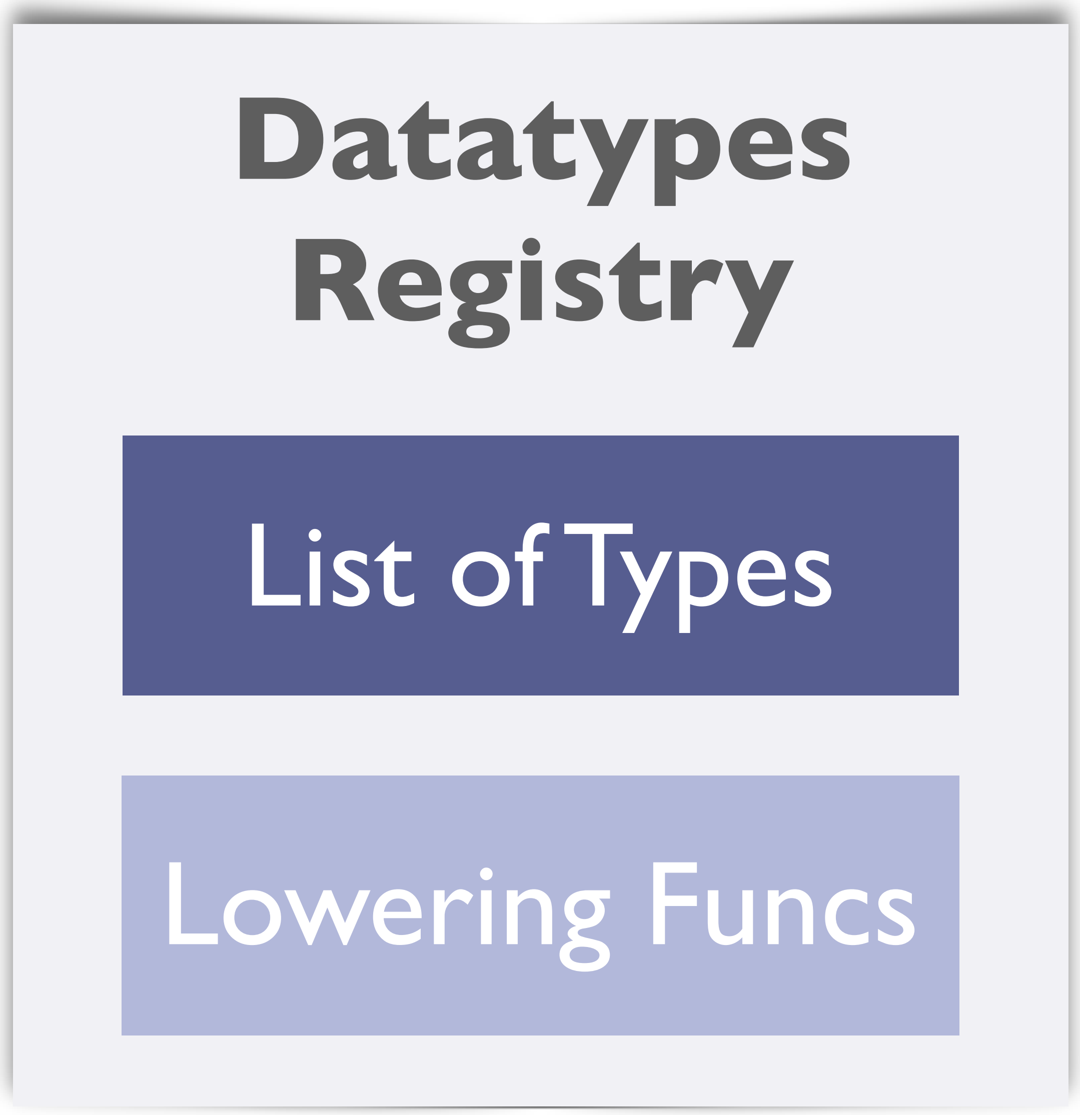

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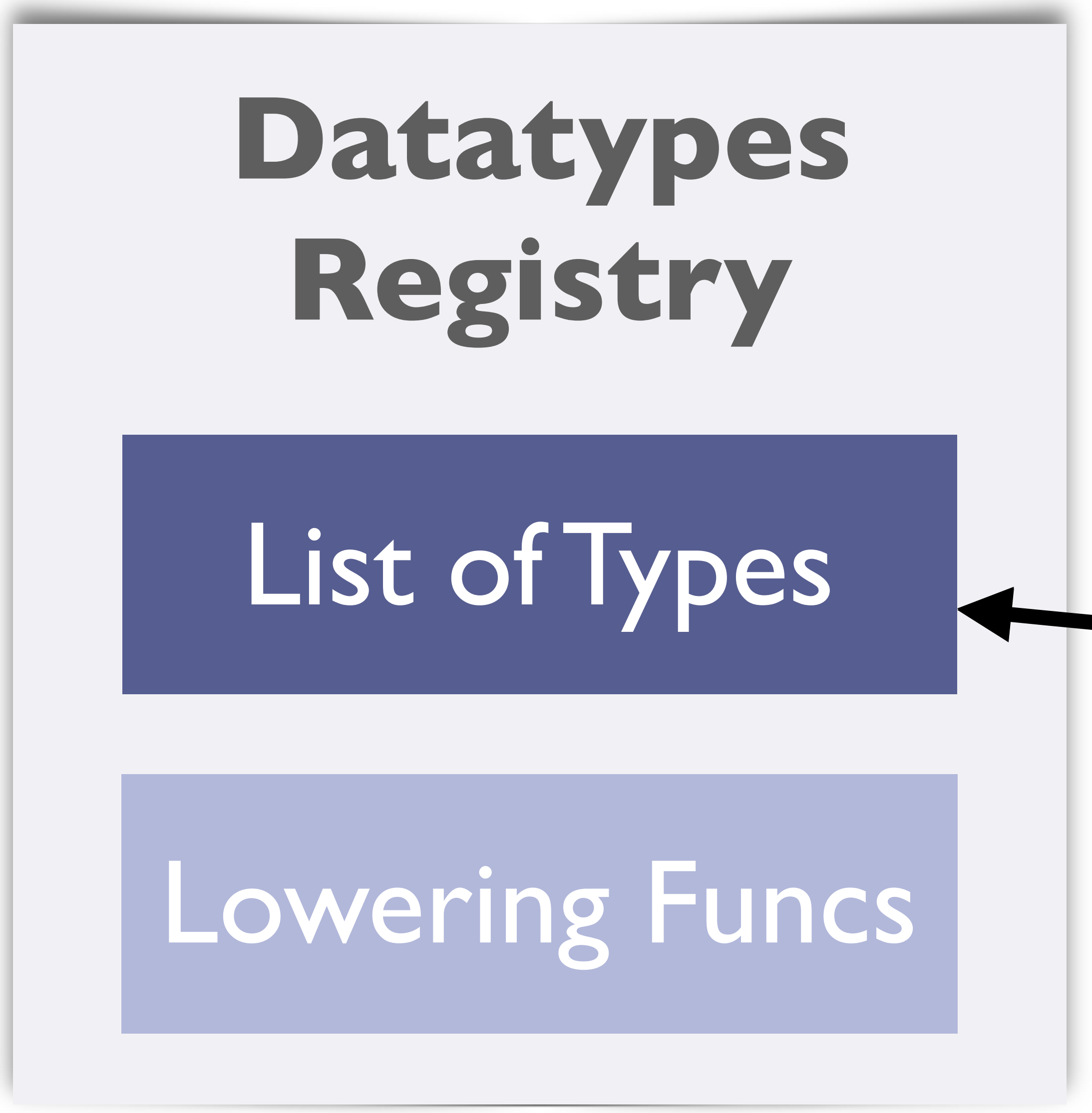

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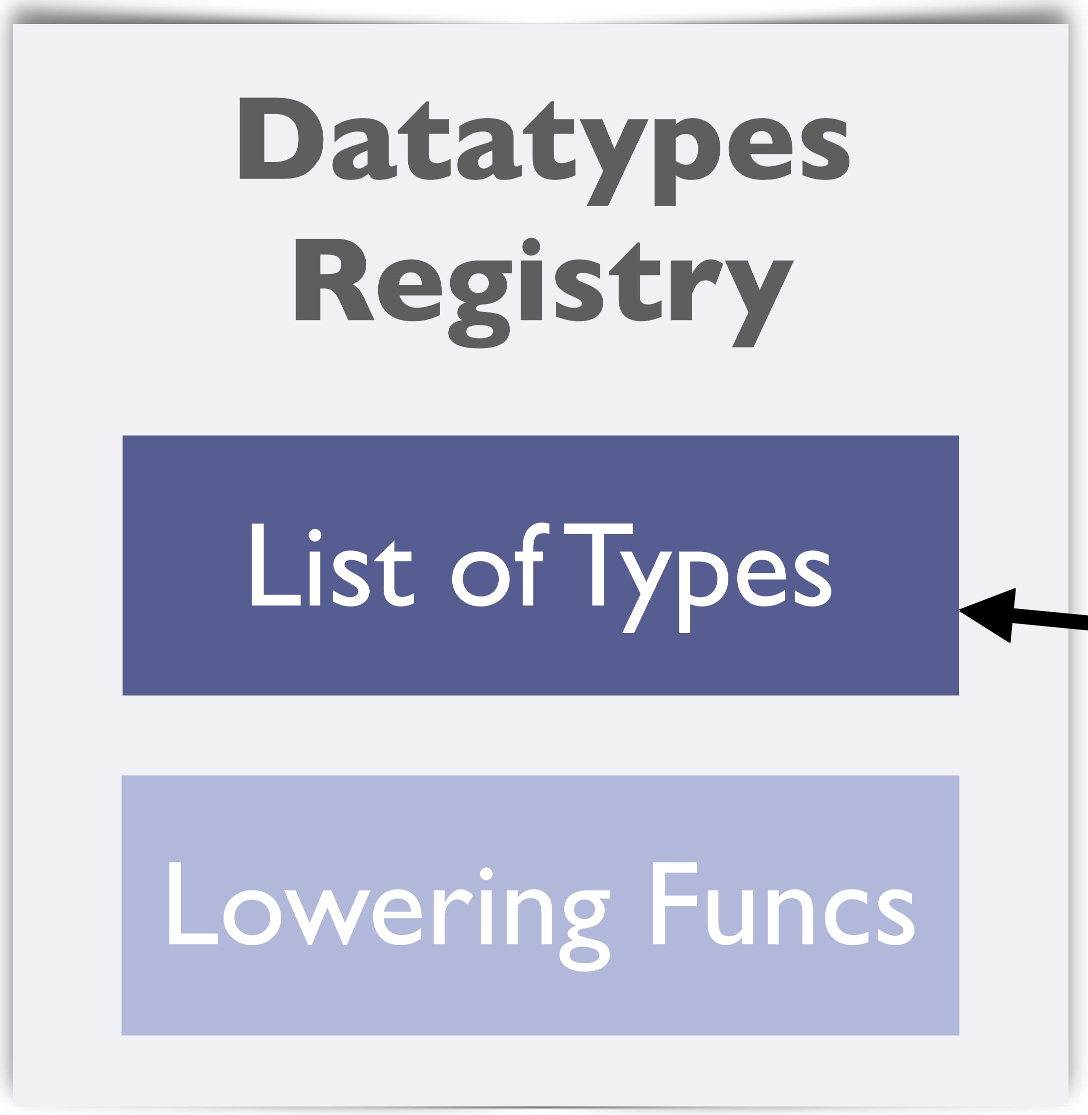

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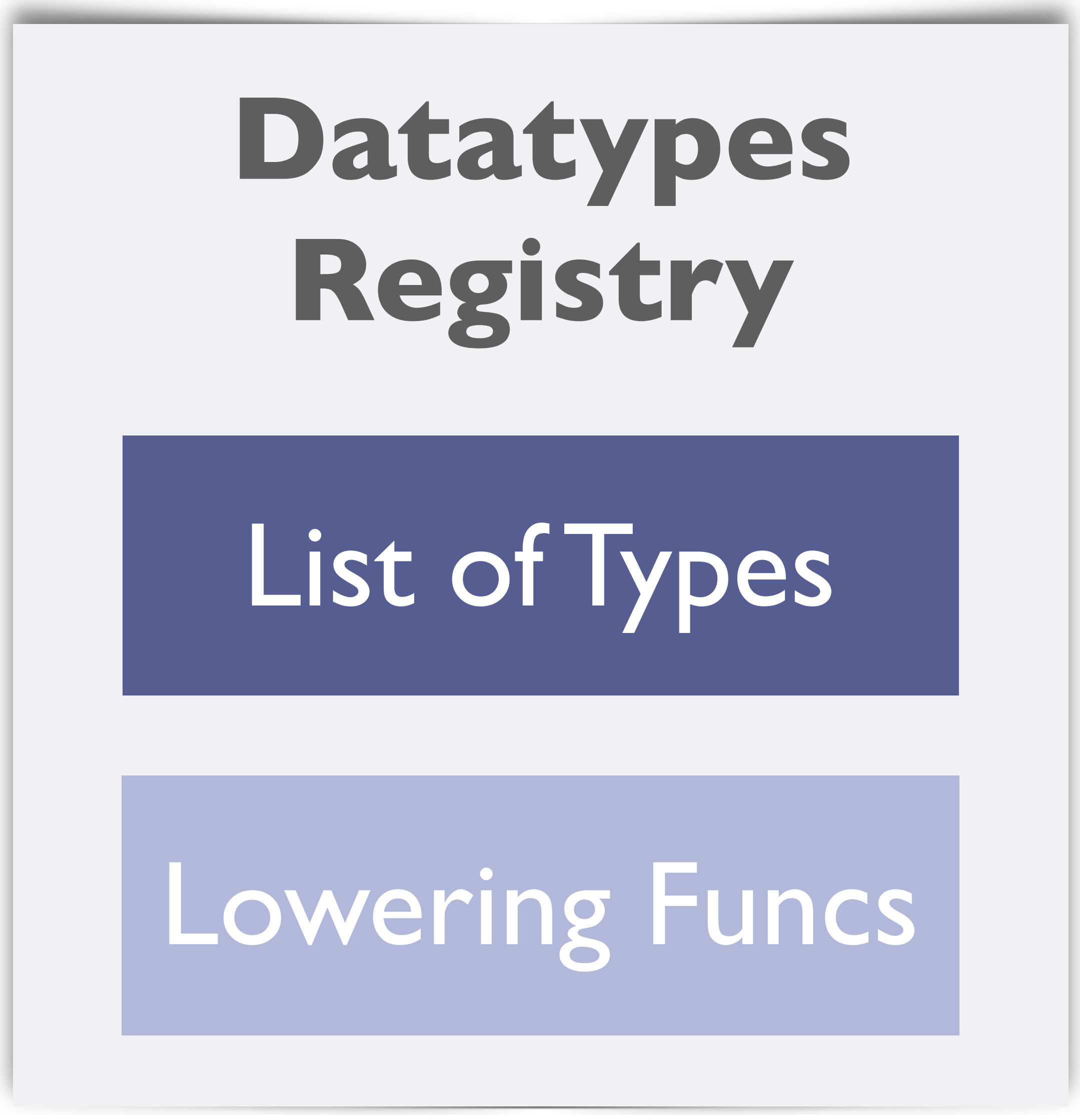
This allows TVM to parse programs which use the datatype!

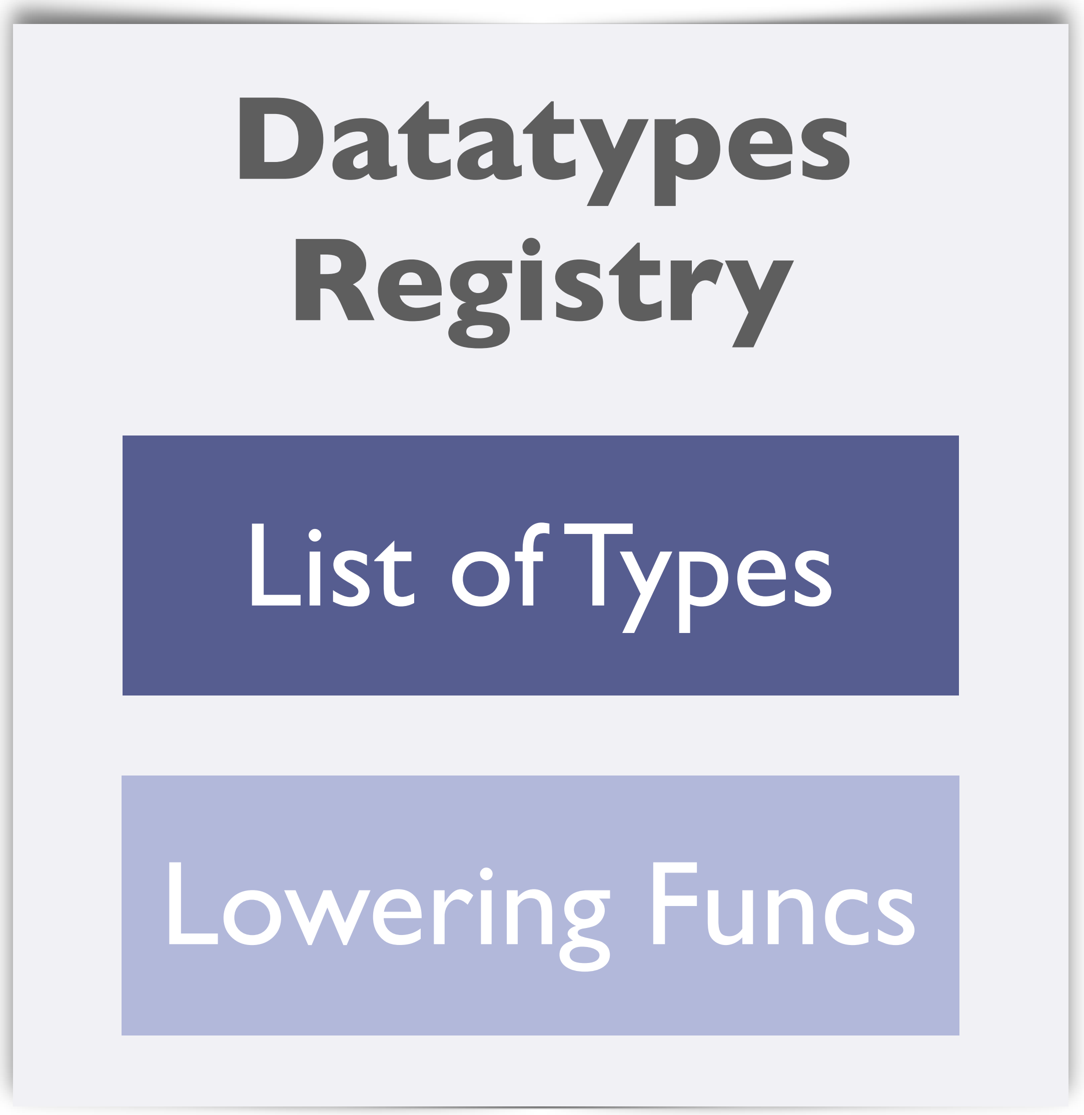
Datatypes Registry

List of Types

Lowering Funcs



Users register lowering functions with a similar API:



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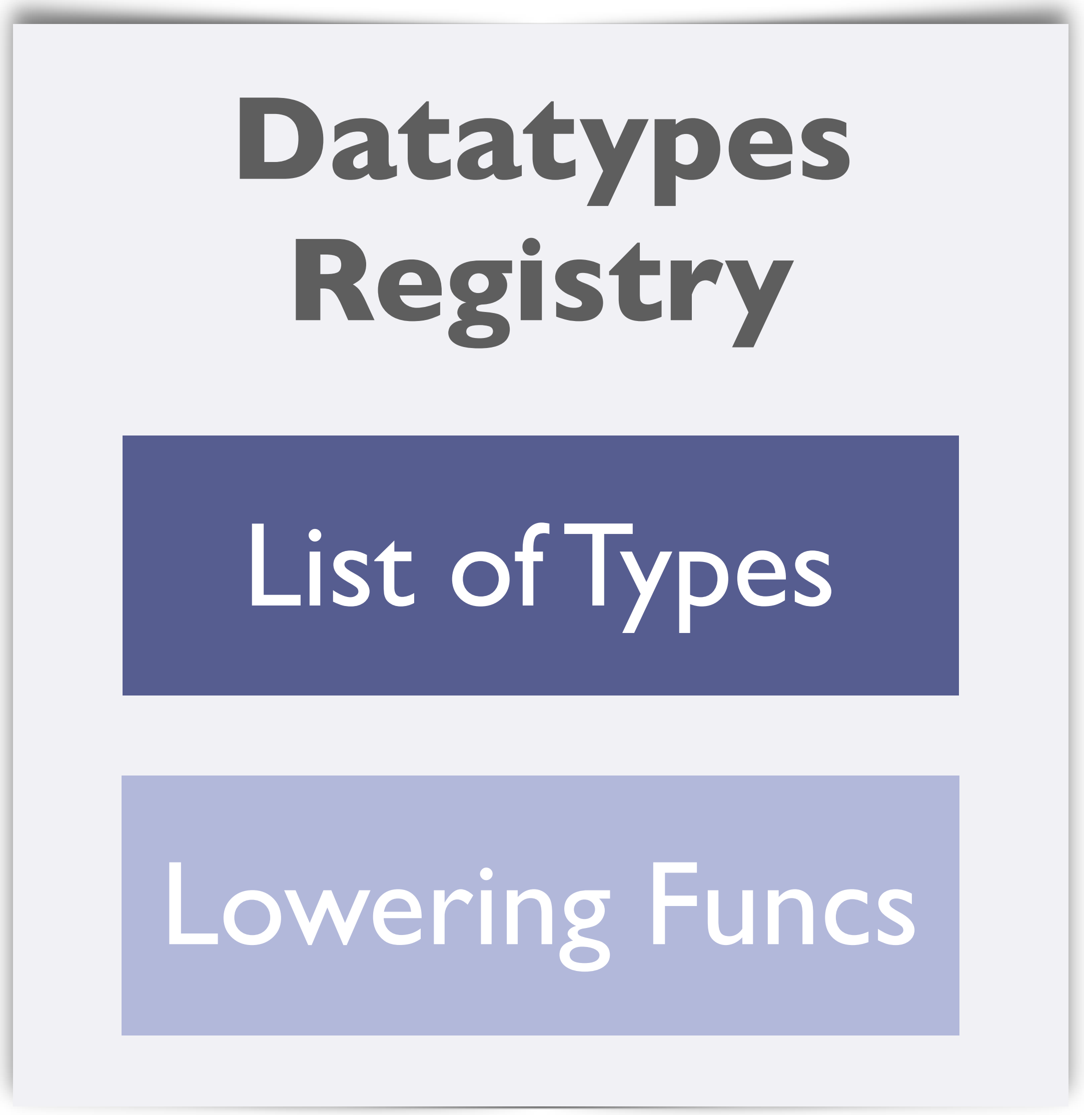

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tvm.datatype.register_op(
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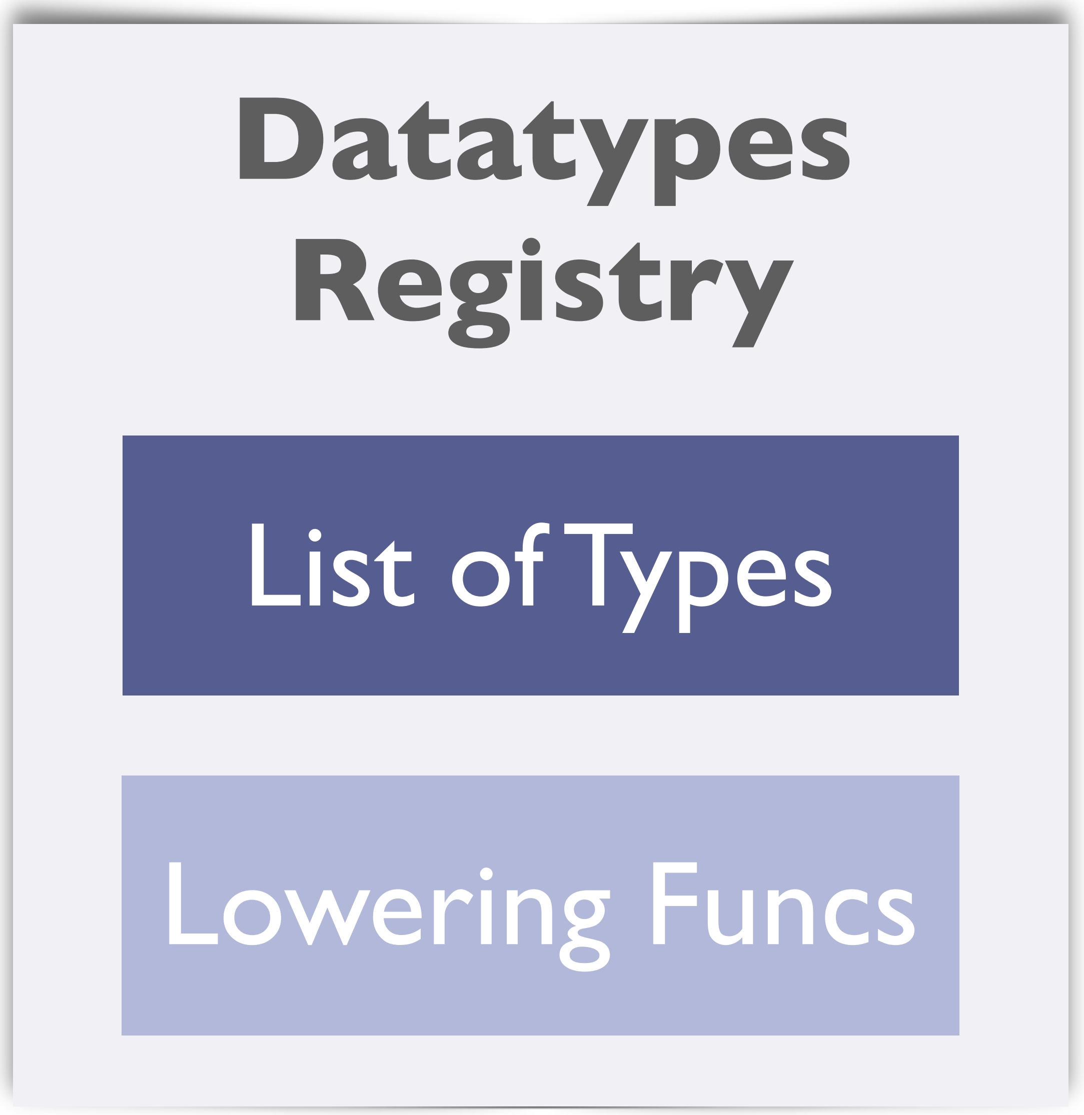

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tvm.datatype.register_op(
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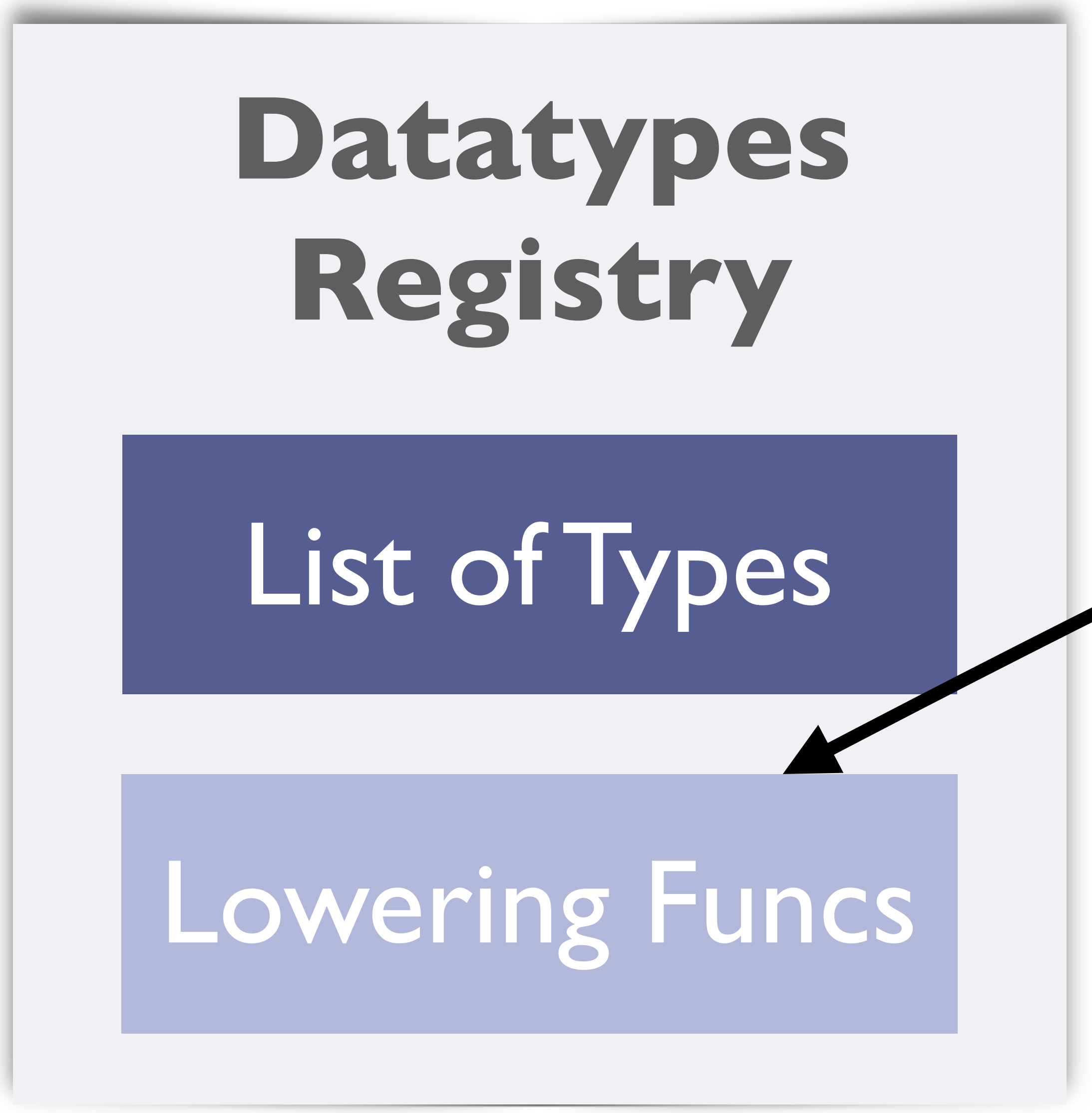

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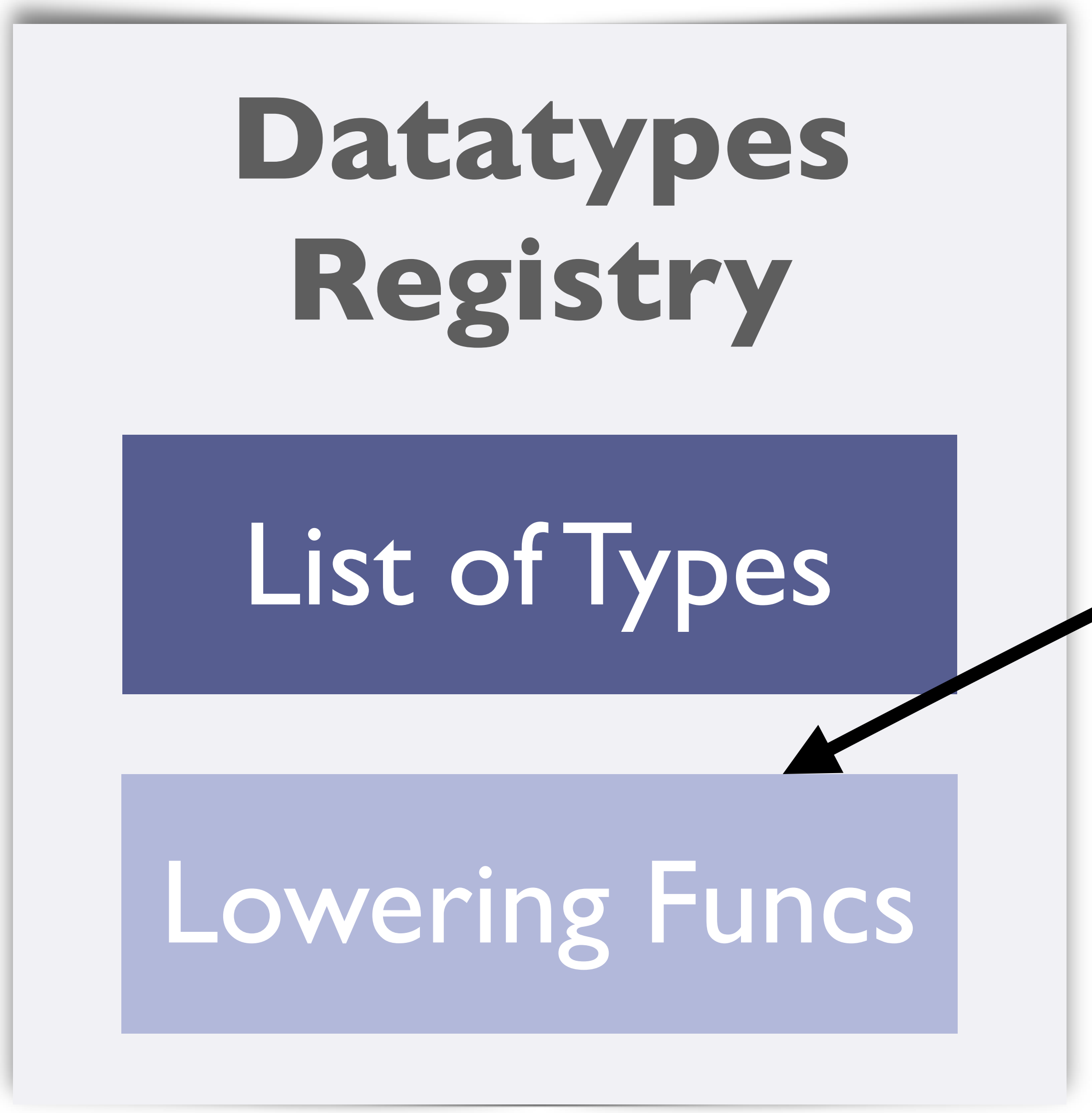

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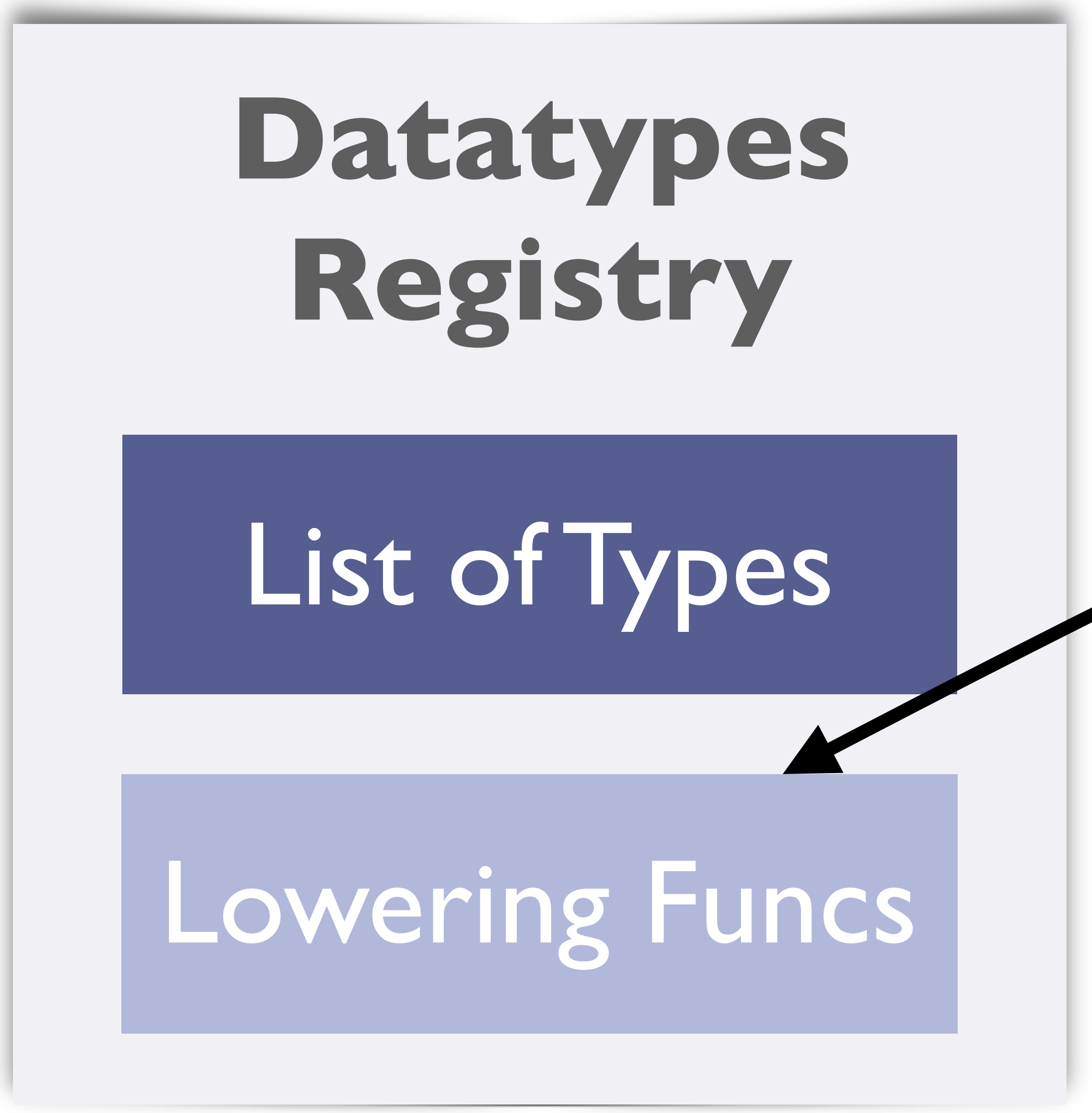

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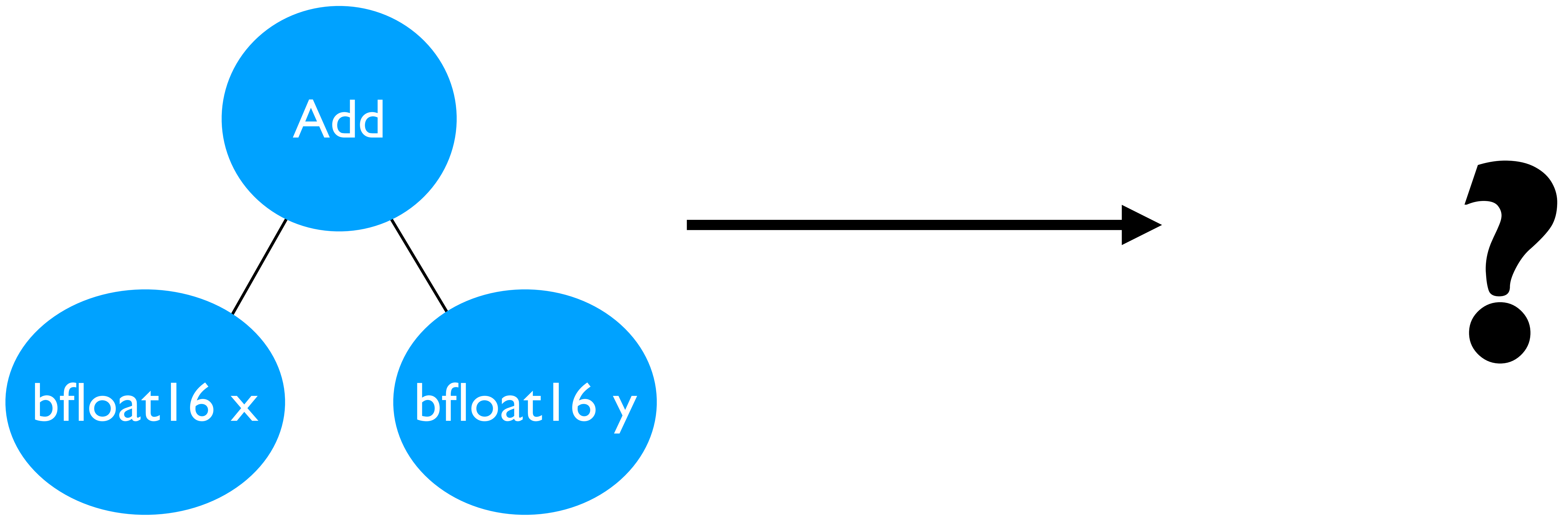
This registers a lowering function which lowers bfloat Adds when compiling to LLVM.

TVM will later use this lowering function when it spits out code!

What do lowering functions look like?



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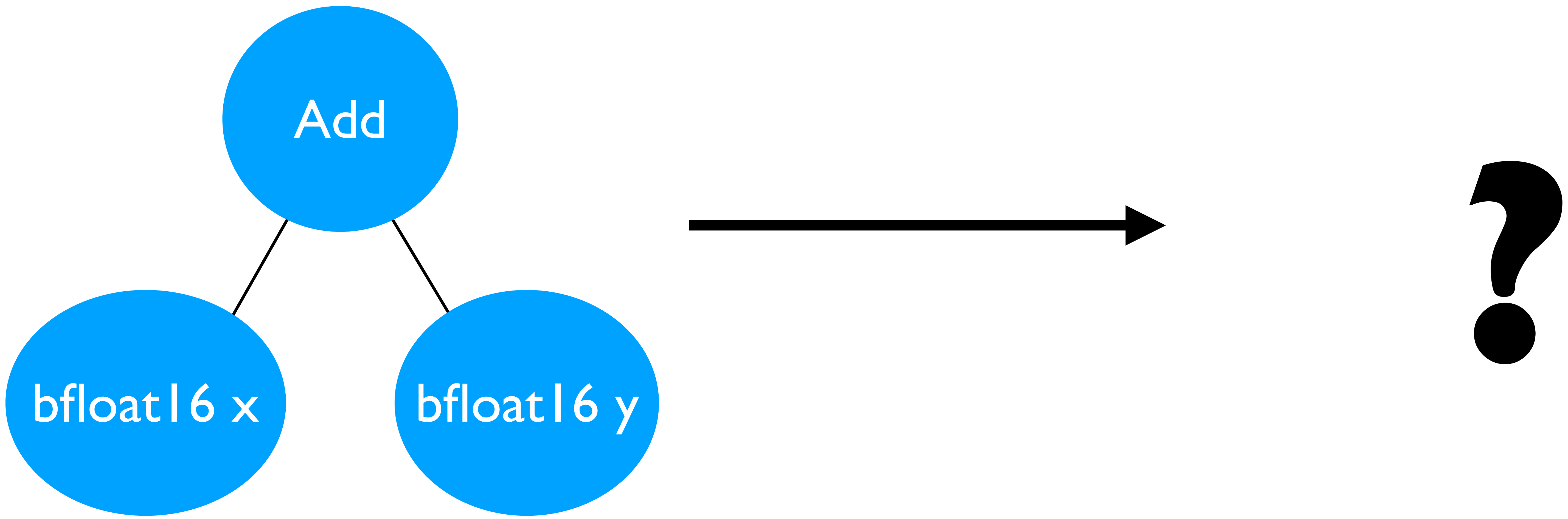

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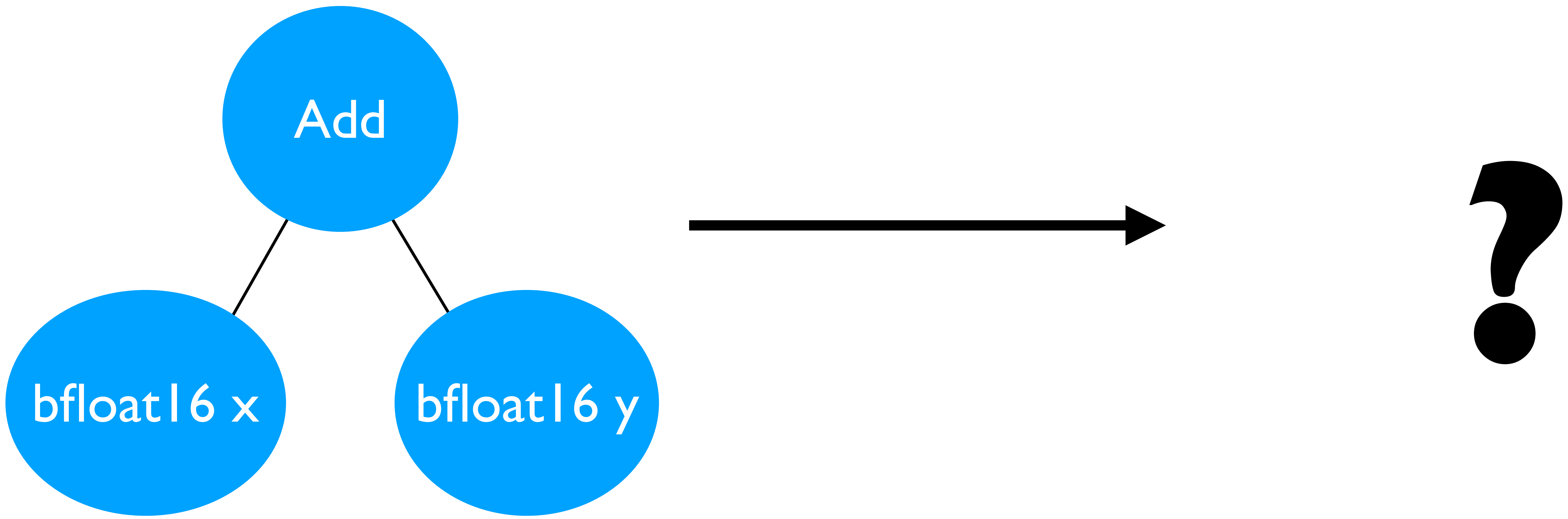

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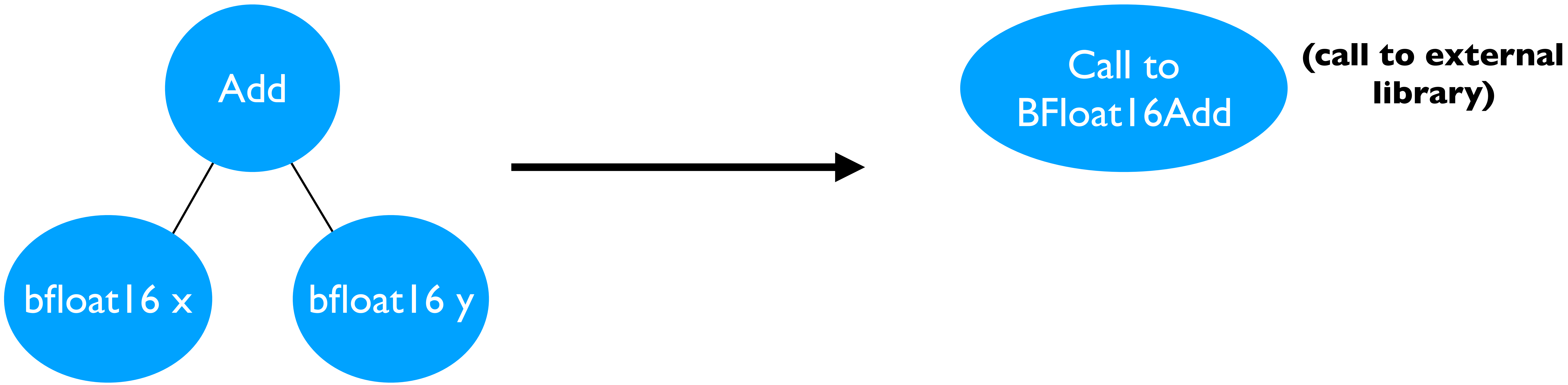

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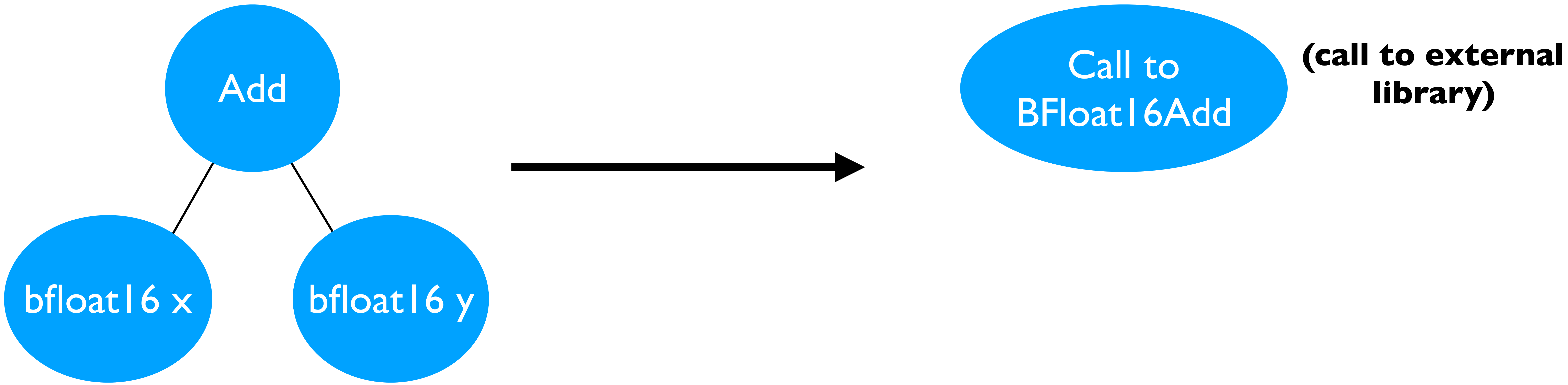

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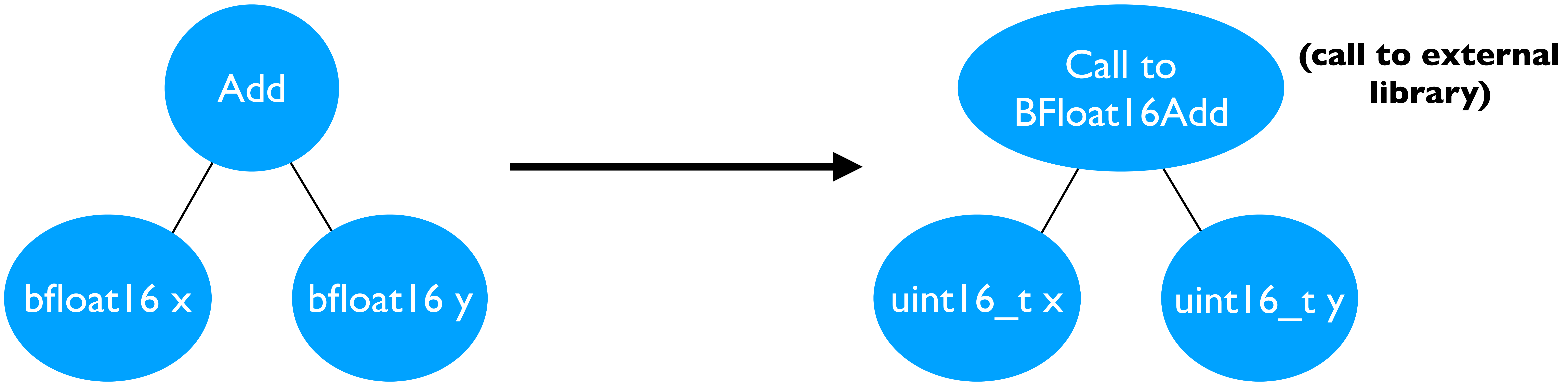

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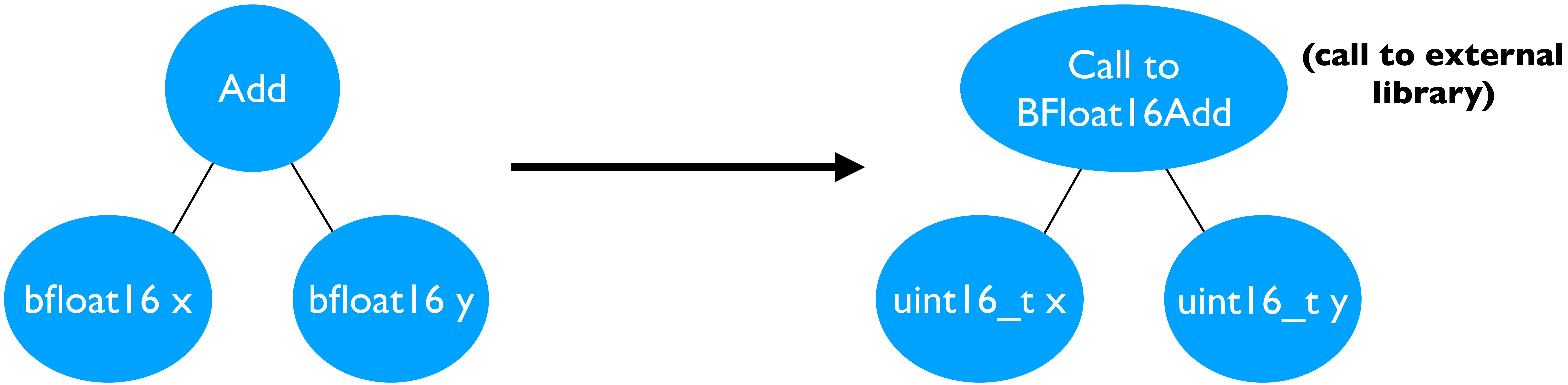

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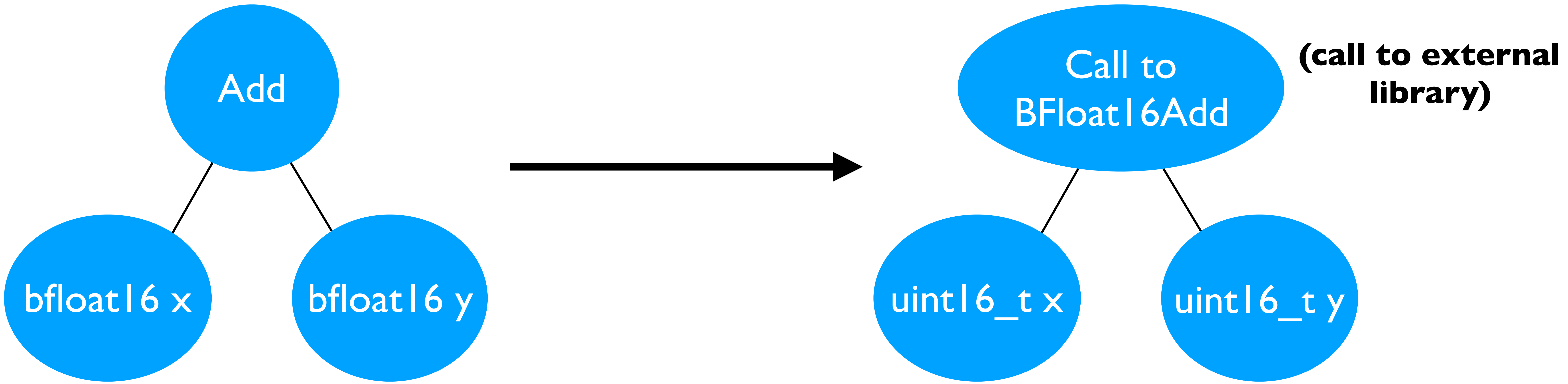

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What do we want?

1. User **makes or finds** a custom datatype library which they'd like to use in deep learning workloads

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   - Lowering functions—user just provides names of library functions!

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Evaluation

To exercise the framework, I decided to conduct a preliminary evaluation of how a model's trained accuracy changes as we change the datatype.

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We will first discuss the experiment itself and its results—then, we will reflect on the utility of the framework.

Experiment Design

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Experiment Design

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4. Ran the models with the converted datatypes over a sample of the CIFAR-10 test set (100 images each) using TVM

Datatypes:

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- "**noptype**": always returns 0

Models:

- MobilenetV1
- Resnet50

Experiment Results and Evaluation

	resnet accuracy	mobilenet accuracy
float32	0.77	0.71
our bfloat16	0.08	0.11
biovault bfloat16	0.1	0.1
Universal posit8	0.08	0.1
Universal posit16	0.77	0.71
Universal posit32	0.77	0.71
libposit posit8	0.08	0.1
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Framework Evaluation

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- Overhead

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- Breadth of datatypes which can be used

Overhead

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- “noptype”: a custom type that does no work

mobilenet v1

	mean inference time (s)	framework overhead
native float32	0.10	1x
float32	0.12	1.11x
noptype	0.11	1.10x

resnet50

	mean inference time (s)	framework overhead
native float32	0.21	1x
float32	0.52	2.51x
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- …but float32 is high-overhead in ResNet → native float32 ResNet much more optimized!

Ease of Use

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  - **3 lines** convert the input, run the model, and convert the output.

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- Implement cleaner registration functions in the TVM Python frontend

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- Block floating point, or any other type with “external” state
- Datatypes with elements larger than 64 bits

Could potentially be implemented by allowing datatypes to attach metadata to each scalar

Future Work

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  - Enable inlining of LLVM
  - Allow users to supply optimized kernels for higher-level operators, e.g. posit conv2d
- Tackle complex datatypes like block floating point

In conclusion, I have presented the Bring Your Own Datatypes framework.

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I have shown how the framework can enable useful datatype research.

Thank You!

Extra Slides

Registering the Datatype

```
import tvm
from tvm import relay
from ctypes import CDLL, RTLD_GLOBAL

CDLL('libposit-wrapper.so', RTLD_GLOBAL)

tvm.datatype.register('posit32', 131)

tvm.datatype.register_op(
    tvm.datatype.create_lower_func('Posit32Add'),
    'Add', 'llvm', 'posit32')
```

Registering the Datatype

✅ **Any loaded C-linkage functions will work!**

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```

✅ **Helper functions for common-case**

Implementing the Datatype

```
#include <cstdint>
#include <posit.h>

posit32_t Uint32ToPosit32(uint32_t in) {
  return posit32_reinterpret(in);
}

uint32_t Posit32ToUint32(posit32_t in) {
  return posit32_bits(in);
}

extern "C" uint32_t Posit32Add(uint32_t a, uint32_t b) {
  auto a_p = Uint32ToPosit32(a);
  auto b_p = Uint32ToPosit32(b);
  auto sum_p = posit32_add(a_p, b_p);
  return Posit32ToUint32(sum_p);
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```

❌ **Inflexible calling convention**

Converting the Program

```python
module, params = load_resnet50()
module, params = change_dtype('float32', 'custom[posit32]32',
                              module['main'], params)

ex = relay.create_executor(mod=module)
model = ex.evaluate()
```

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✅ **Changing datatype of a program is easy!**

Running the Program

```python
image = ... # load image

image = convert_ndarray('custom[posit32]32', image)

with tvm.build_config(disable_vectorize=True):
    output = model(image, **params)

output = convert_ndarray('float32', output)
```

Running the Program

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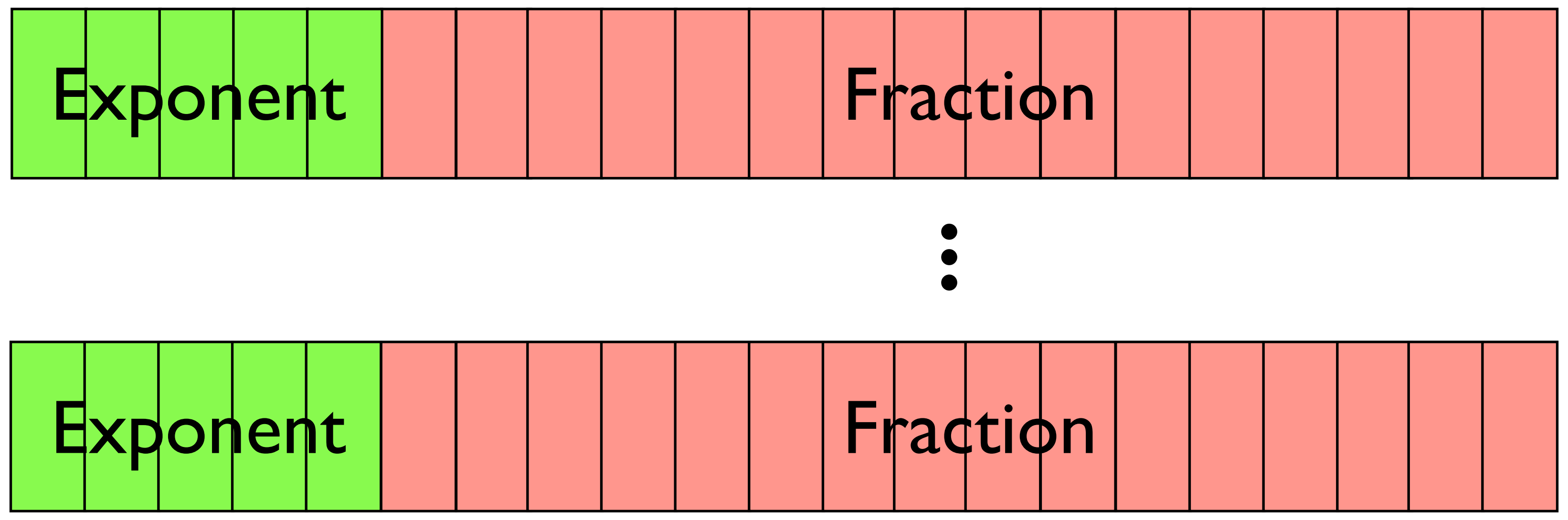
✅ **Converting data is also easy!**

❌ **Have to manually disable vectorization**

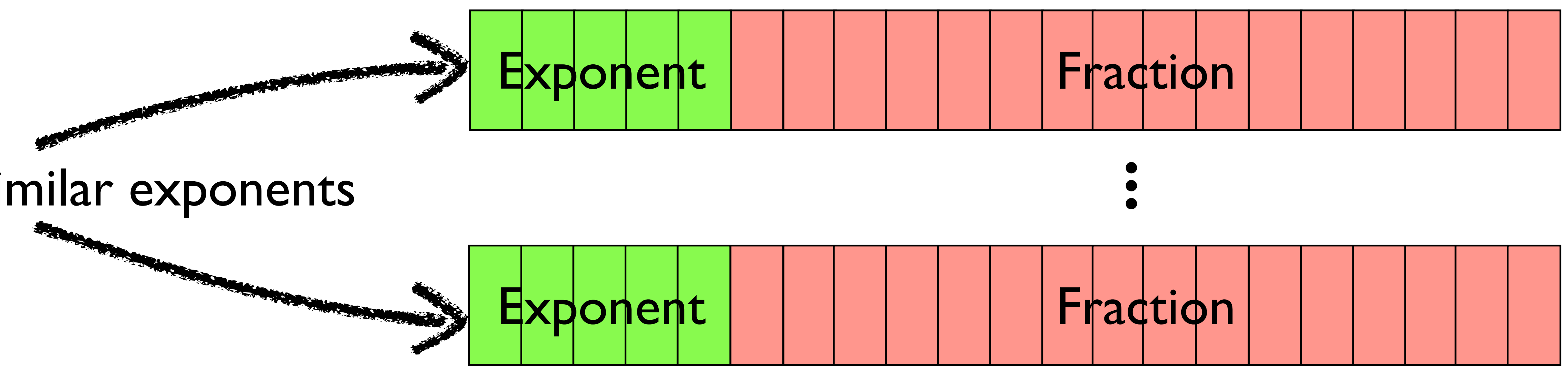
Flexpoint



See Köster et. al., “An Adaptive Numerical Format for Efficient Training of Deep Neural Networks”

Flexpoint

Similar magnitude → similar exponents



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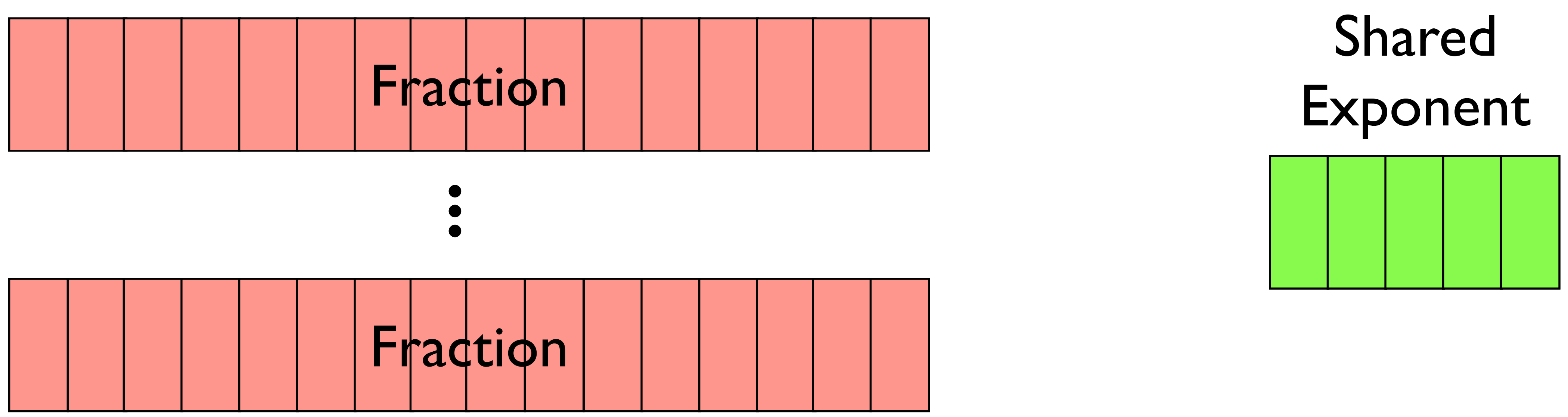

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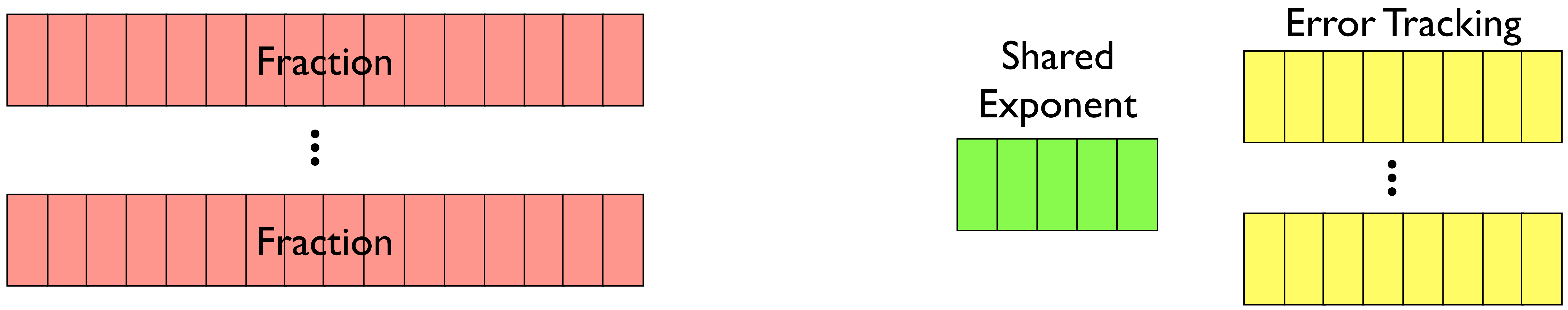

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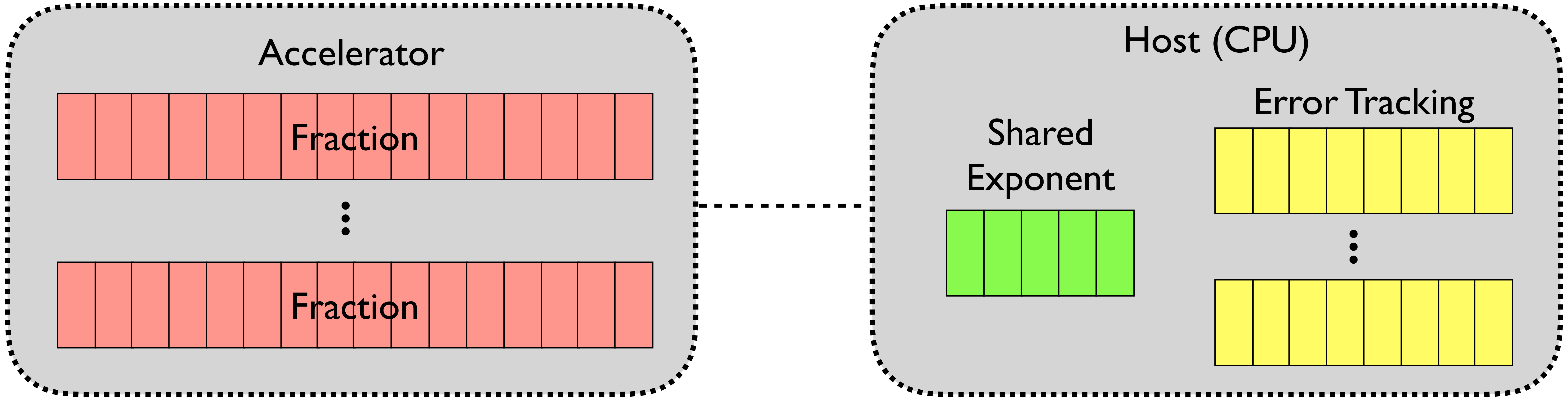

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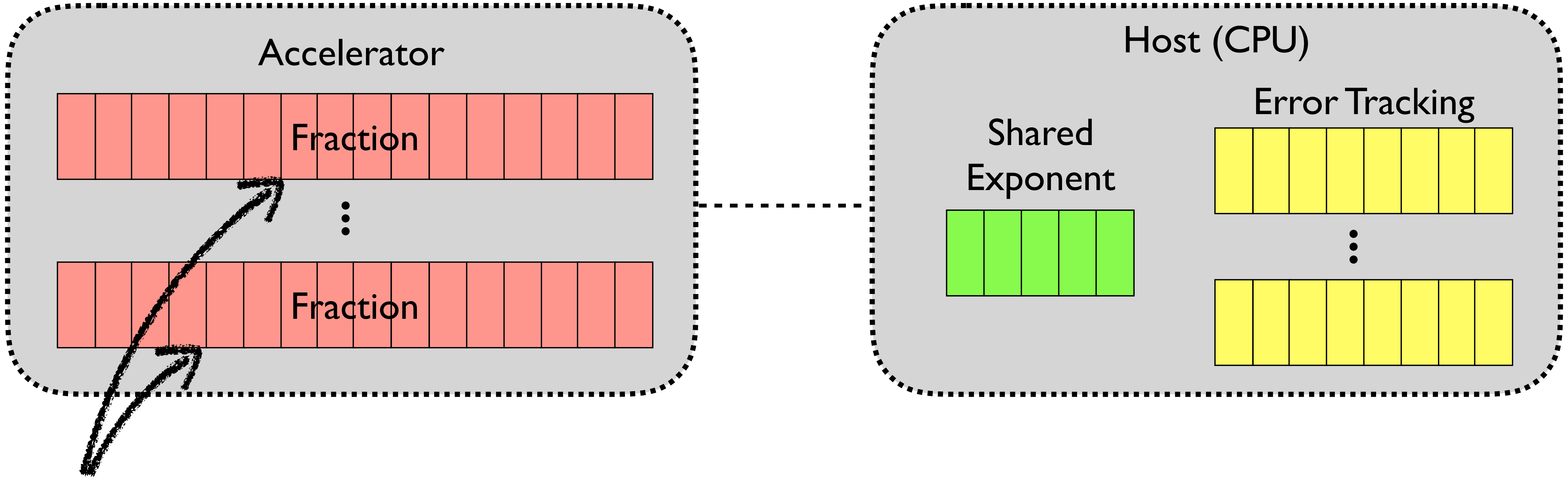

Just integers! We can use integer hardware!

See Köster et. al., “An Adaptive Numerical Format for Efficient Training of Deep Neural Networks”