Optimised Deep Learning on Jean Zay (DLO-JZ)

Torch & Compilation

Institut du Développement et des Ressources en Informatique Scientifique

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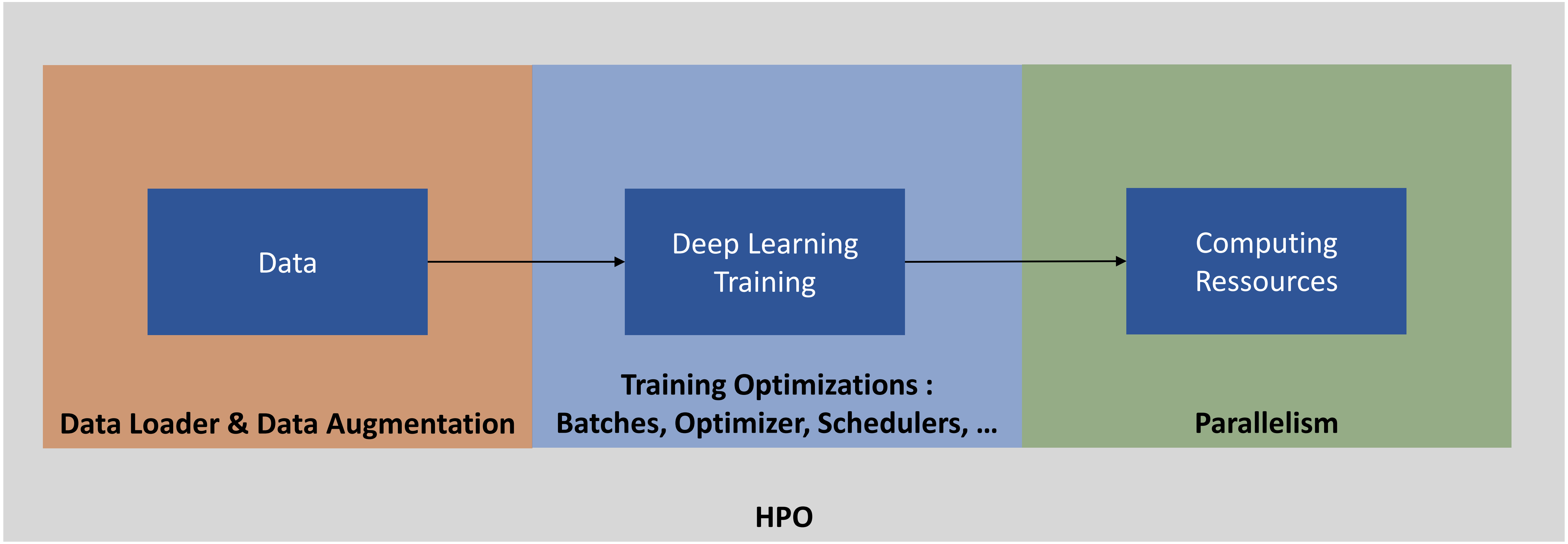
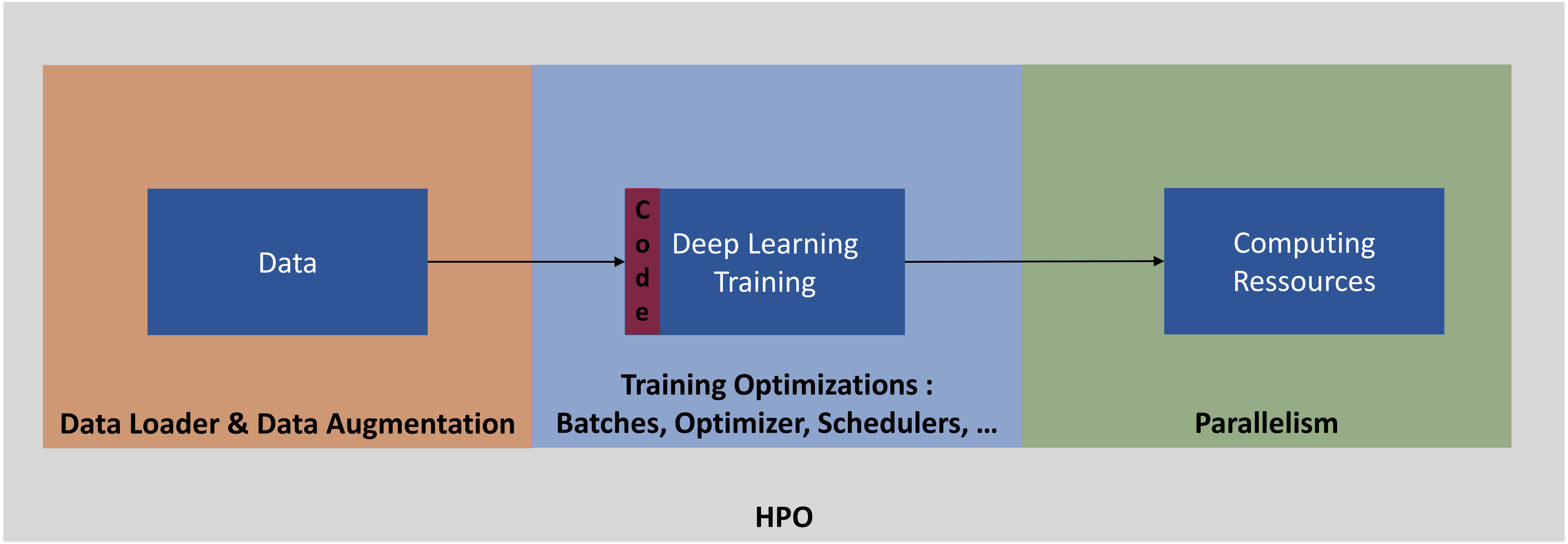

Data
Deep Learning Training
Computing Ressources
Data Loader & Data Augmentation
Training Optimizations : Batches, Optimizer, Schedulers, …
Parallelism
HPO

Optimize everything ?


Data
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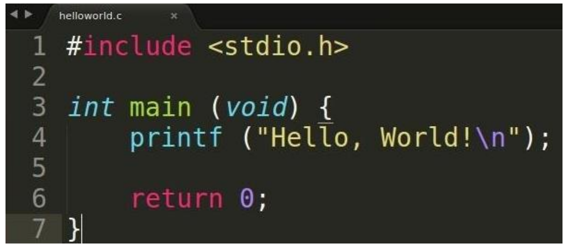
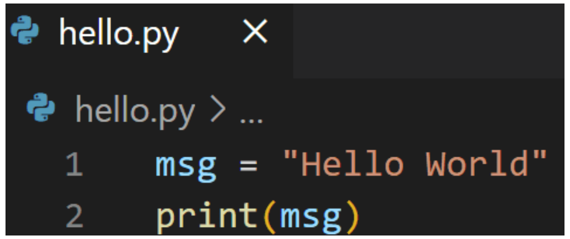
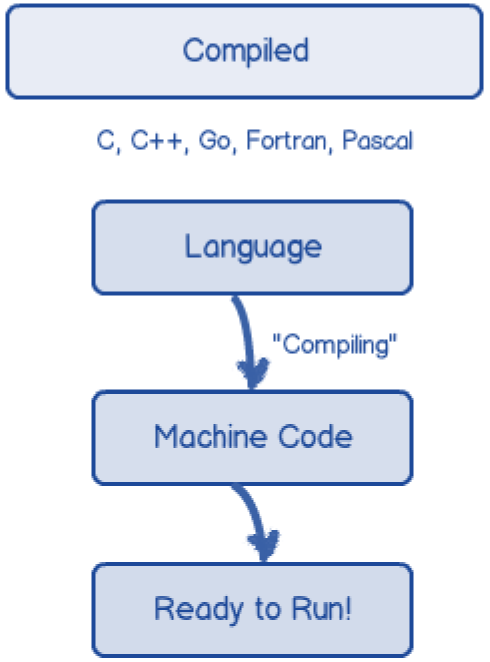
Optimize everything !

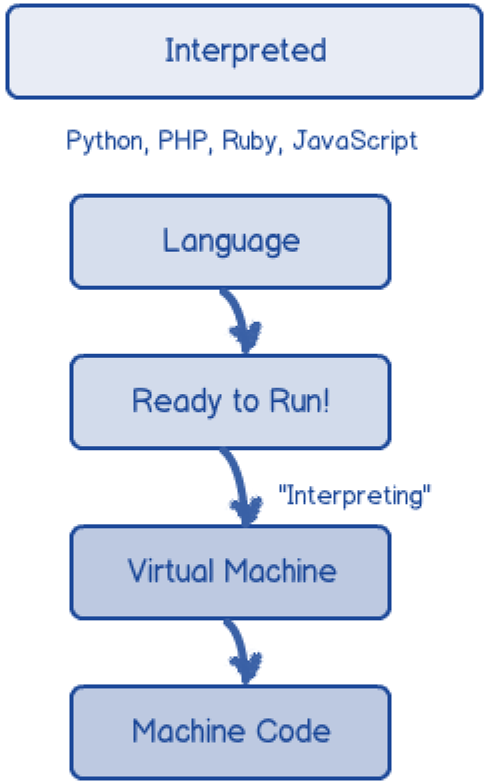


```c
#include <stdio.h>

int main (void) {
    printf ("Hello, World!\n");

    return 0;
}
```

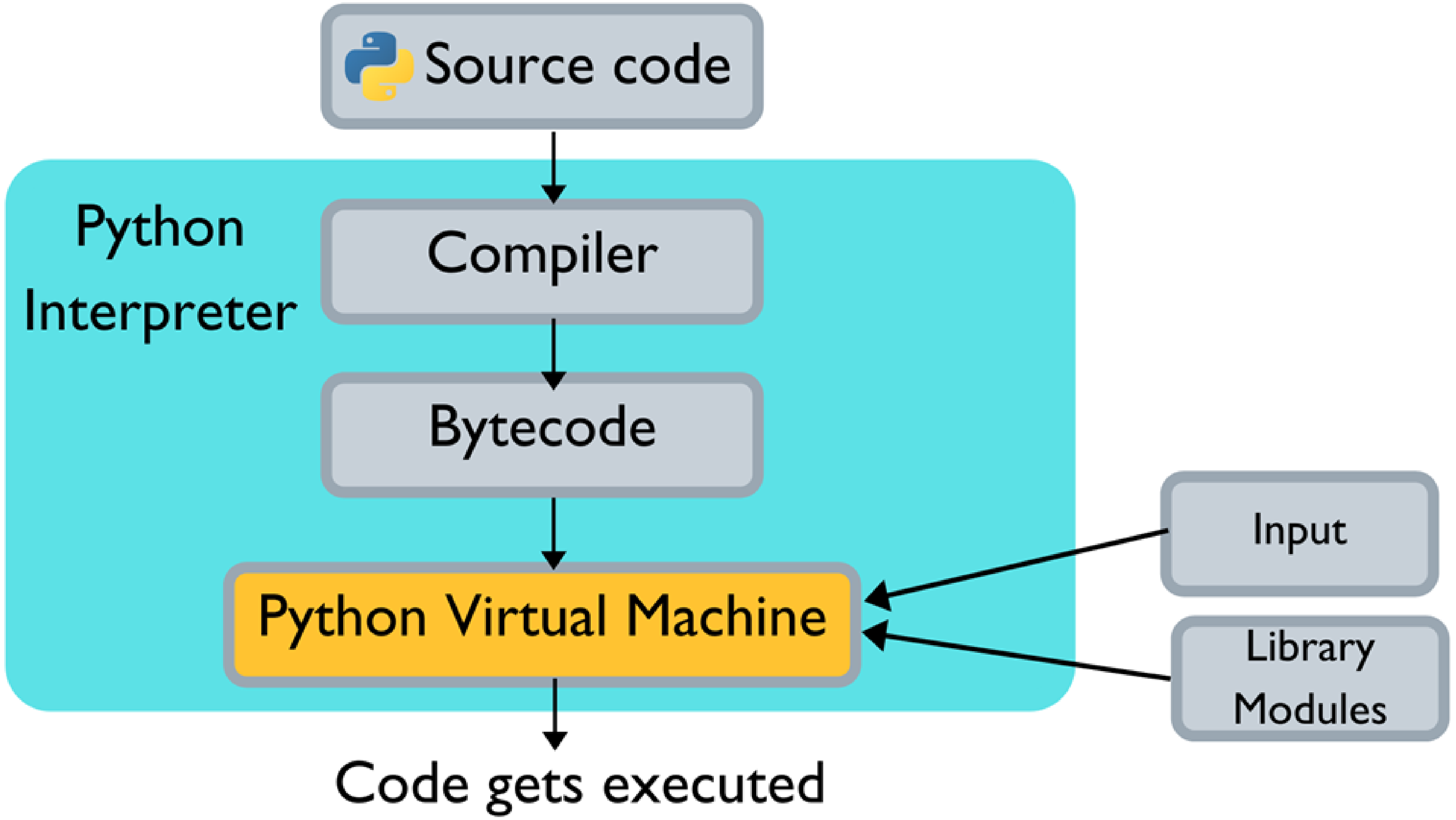


```python
msg = "Hello World"
print(msg)
```

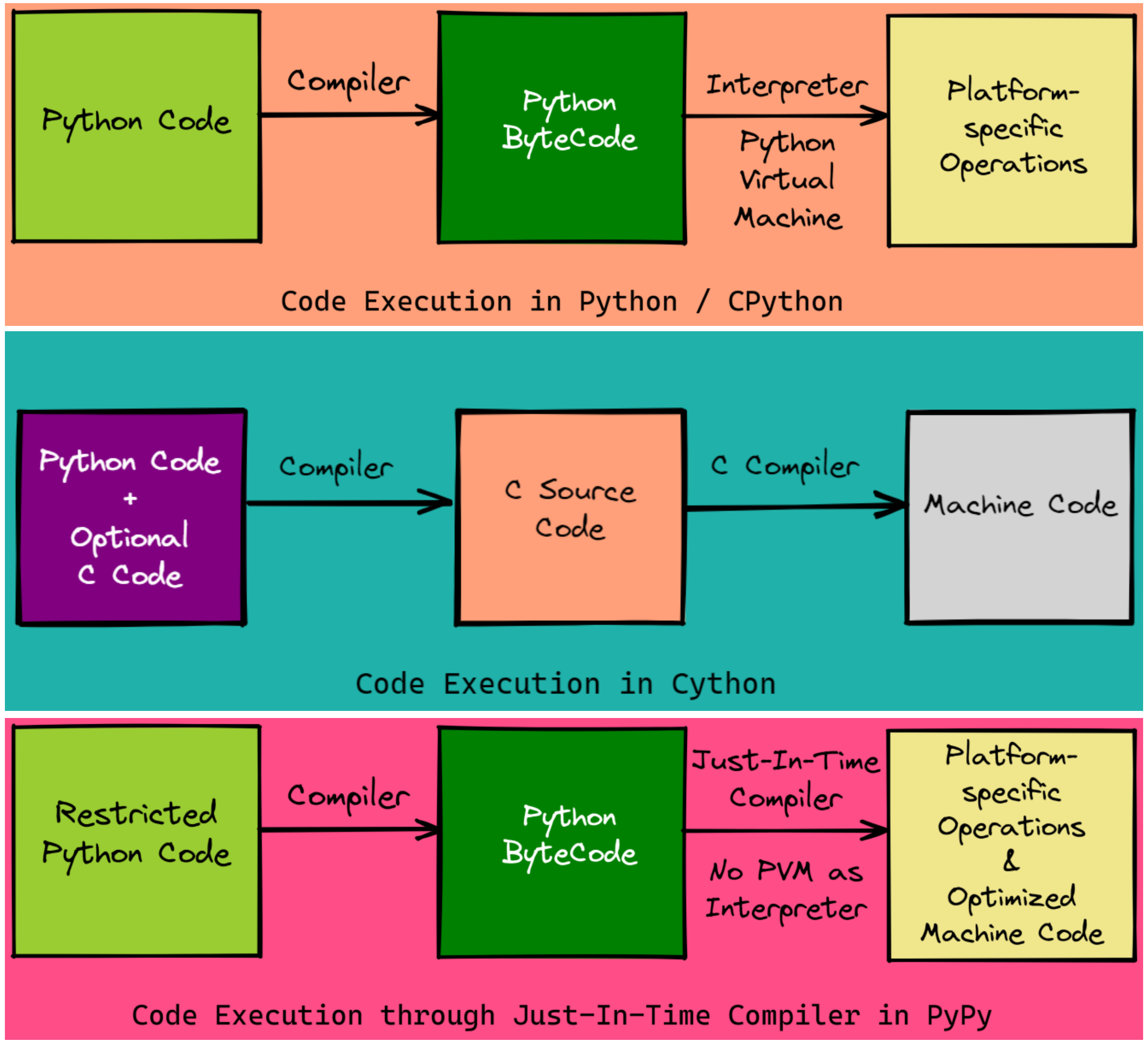




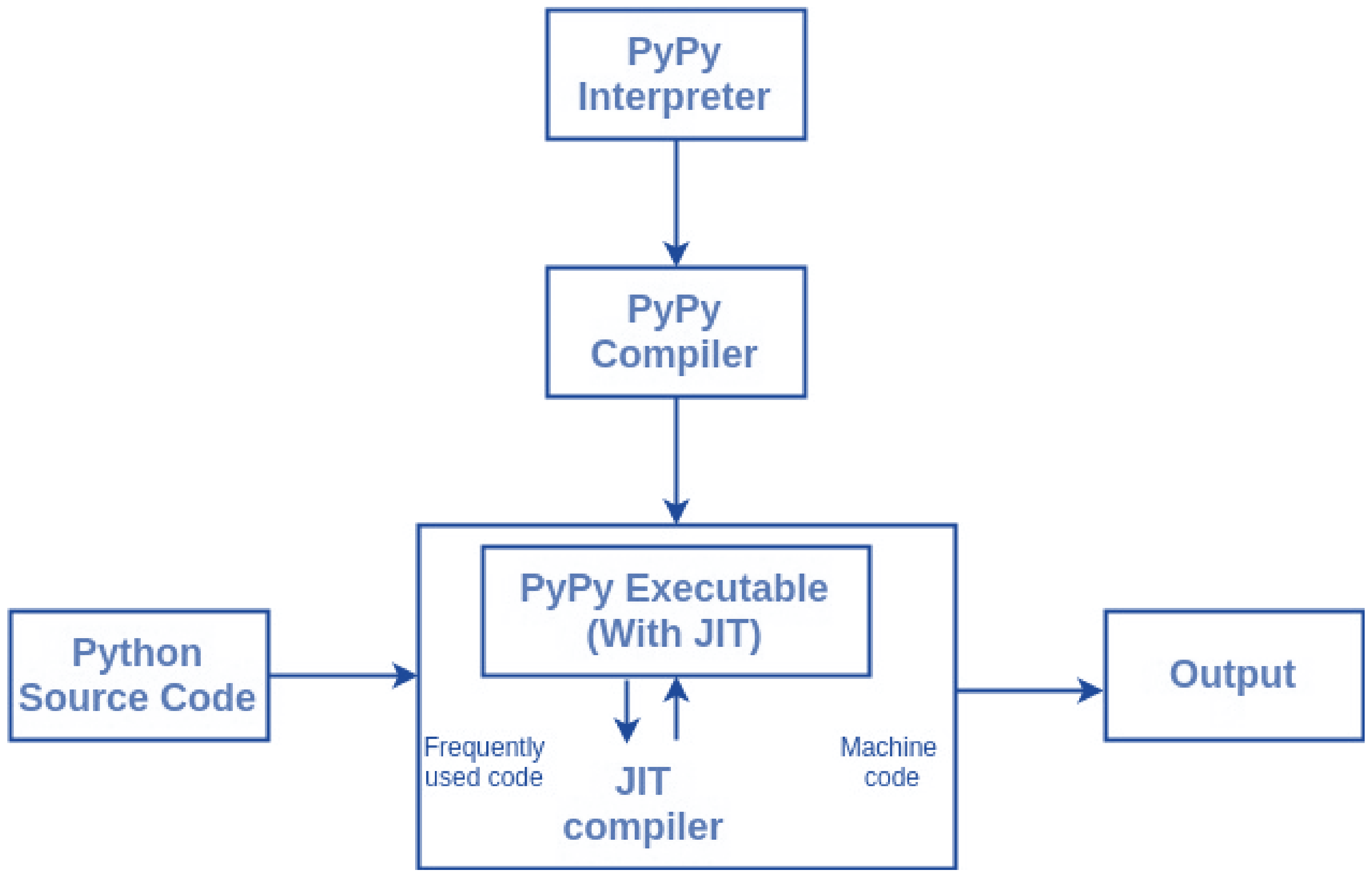
Code?



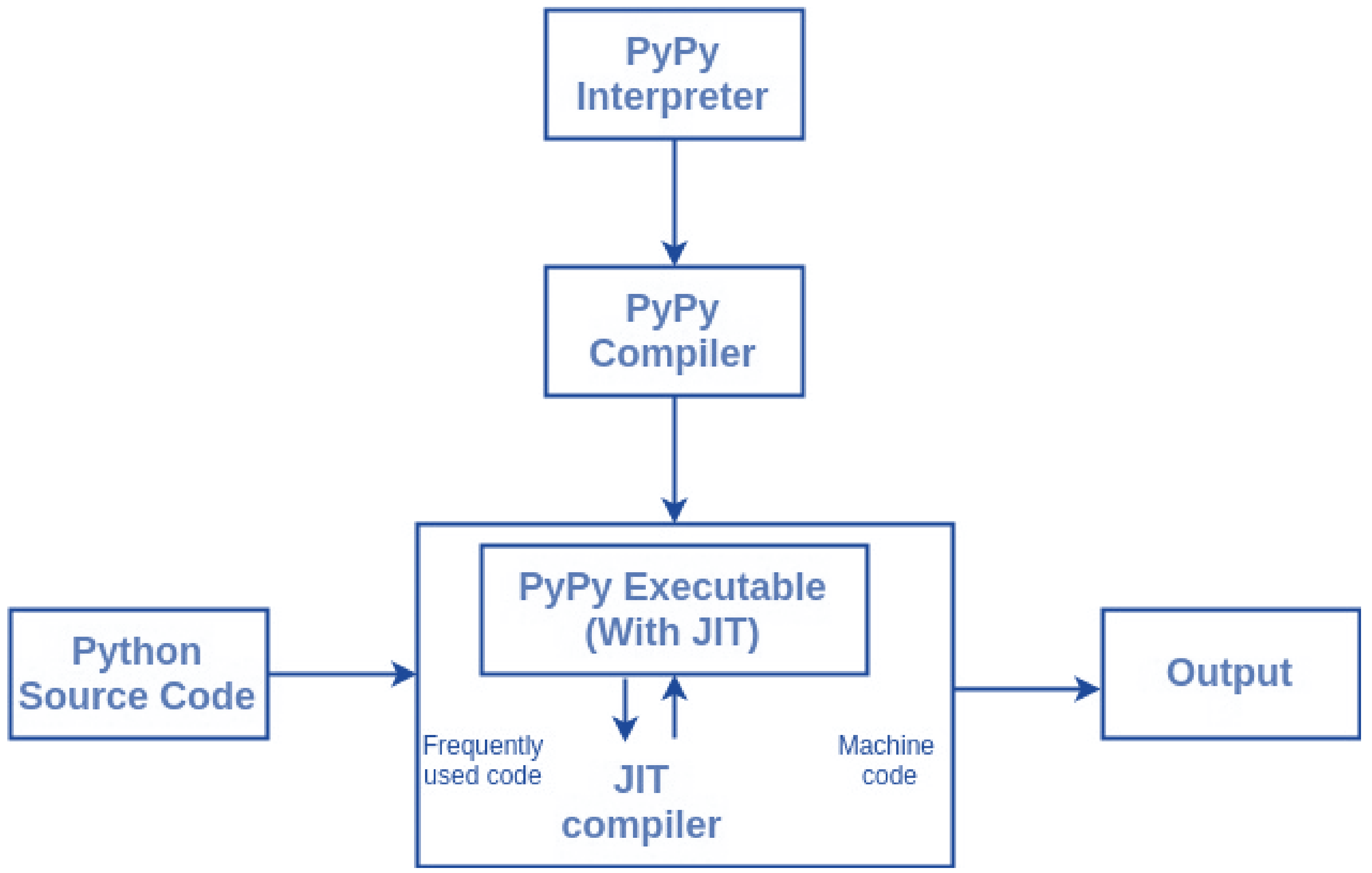
Python ? CPython !



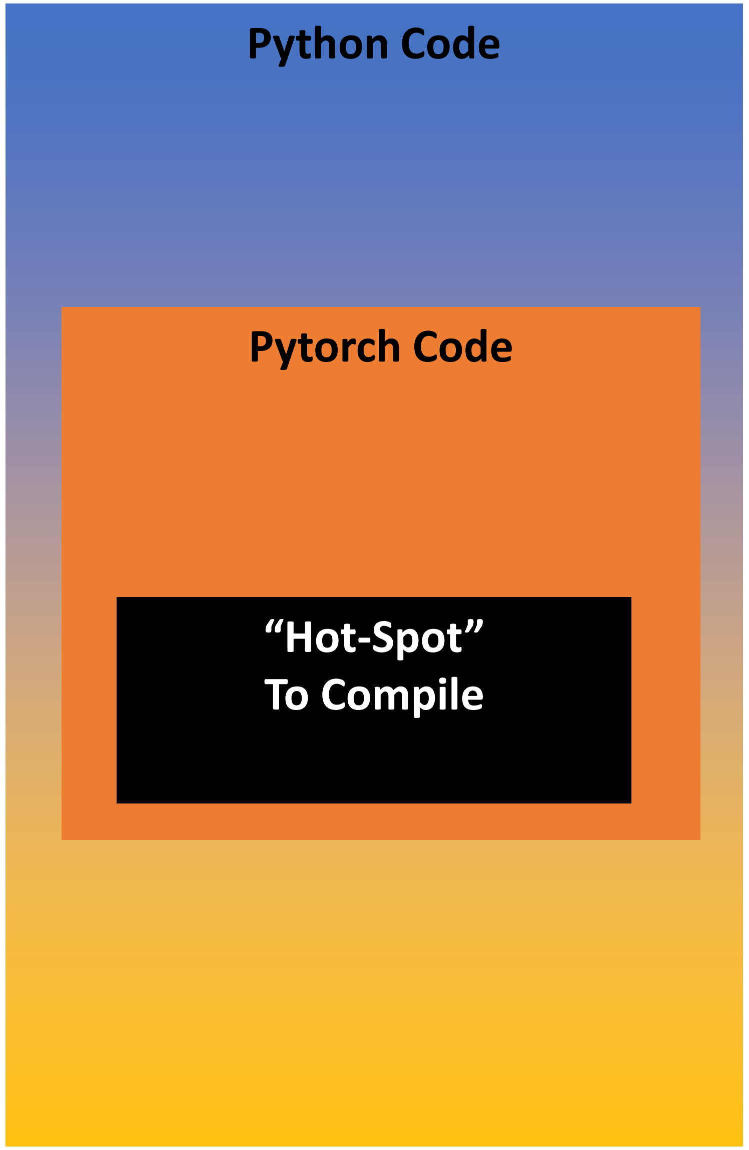
Cpython, Jython, Cython, PyPy



Just-In-Time Compilation



Just-In-Time Compilation – Python Level



Internal Pytorch JIT:

TorchScript

Torch Compile

Just-In-Time Compilation – Pytorch Level

```python
import torch
class MyCell(torch.nn.Module):
    def __init__(self):
        super(MyCell, self).__init__()
        self.linear = torch.nn.Linear(4, 4)

    def forward(self, x, h):
        new_h = torch.tanh(self.linear(x) + h)
        return new_h, new_h

x, h = torch.rand(3, 4), torch.rand(3, 4)
my_cell = MyCell()
my_cell(x, h)
```

Tracing

```python
traced_cell = torch.jit.trace(my_cell, (x, h))
traced_cell(x, h)
print(traced_cell.code)
```

```
def forward(self,
    x: Tensor,
    h: Tensor) -> Tuple[Tensor, Tensor]:
  linear = self.linear
  _0 = torch.tanh(torch.add((linear).forward(x, ), h))
  return (_0, _0)
```

TorchScript – Tracing

```python
class MyDecisionGate(torch.nn.Module):
    def forward(self, x):
        if x.sum() > 0:
            return x
        else:
            return -x

class MyCell(torch.nn.Module):
    def __init__(self, dg):
        super(MyCell, self).__init__()
        self.dg = dg
        self.linear = torch.nn.Linear(4, 4)

    def forward(self, x, h):
        new_h = torch.tanh(self.dg(self.linear(x)) + h)
        return new_h, new_h

my_cell = MyCell(MyDecisionGate())
traced_cell = torch.jit.trace(my_cell, (x, h))
```

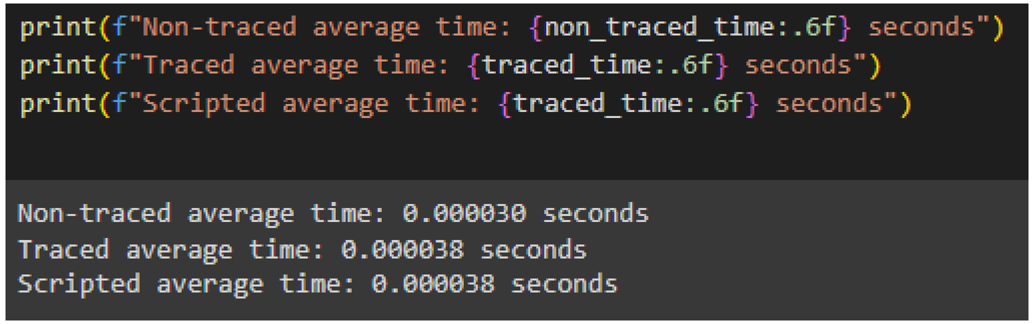
TracerWarning: Converting a tensor to a Python boolean might cause the trace to be incorrect. We can't record the data flow of Python values, so this value will be treated as a constant in the future. This means that the trace might not generalize to other inputs!

Scripting

```python
scripted_gate = torch.jit.script(MyDecisionGate())

my_cell = MyCell(scripted_gate)
scripted_cell = torch.jit.script(my_cell)
```

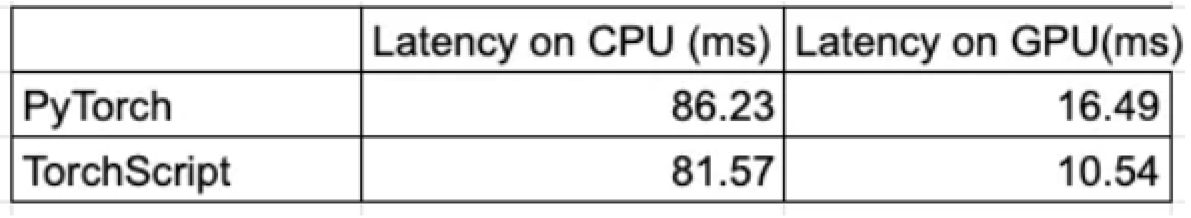
TorchScript – Scripting

TorchScript – Performance



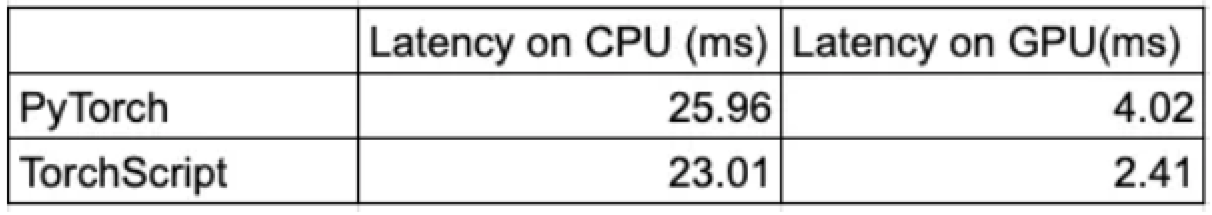
```
print(f"Non-traced average time: {non_traced_time:.6f} seconds")
print(f"Traced average time: {traced_time:.6f} seconds")
print(f"Scripted average time: {traced_time:.6f} seconds")
```

```
Non-traced average time: 0.000030 seconds
Traced average time: 0.000038 seconds
Scripted average time: 0.000038 seconds
```



	Latency on CPU (ms)	Latency on GPU(ms)
PyTorch	86.23	16.49
TorchScript	81.57	10.54

PyTorch vs TorchScript for BERT

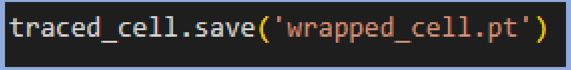


	Latency on CPU (ms)	Latency on GPU(ms)
PyTorch	25.96	4.02
TorchScript	23.01	2.41

PyTorch vs TorchScript for ResNet

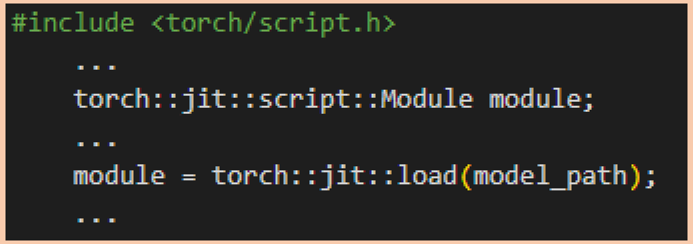
TorchScript – Save & Load

Save in Python

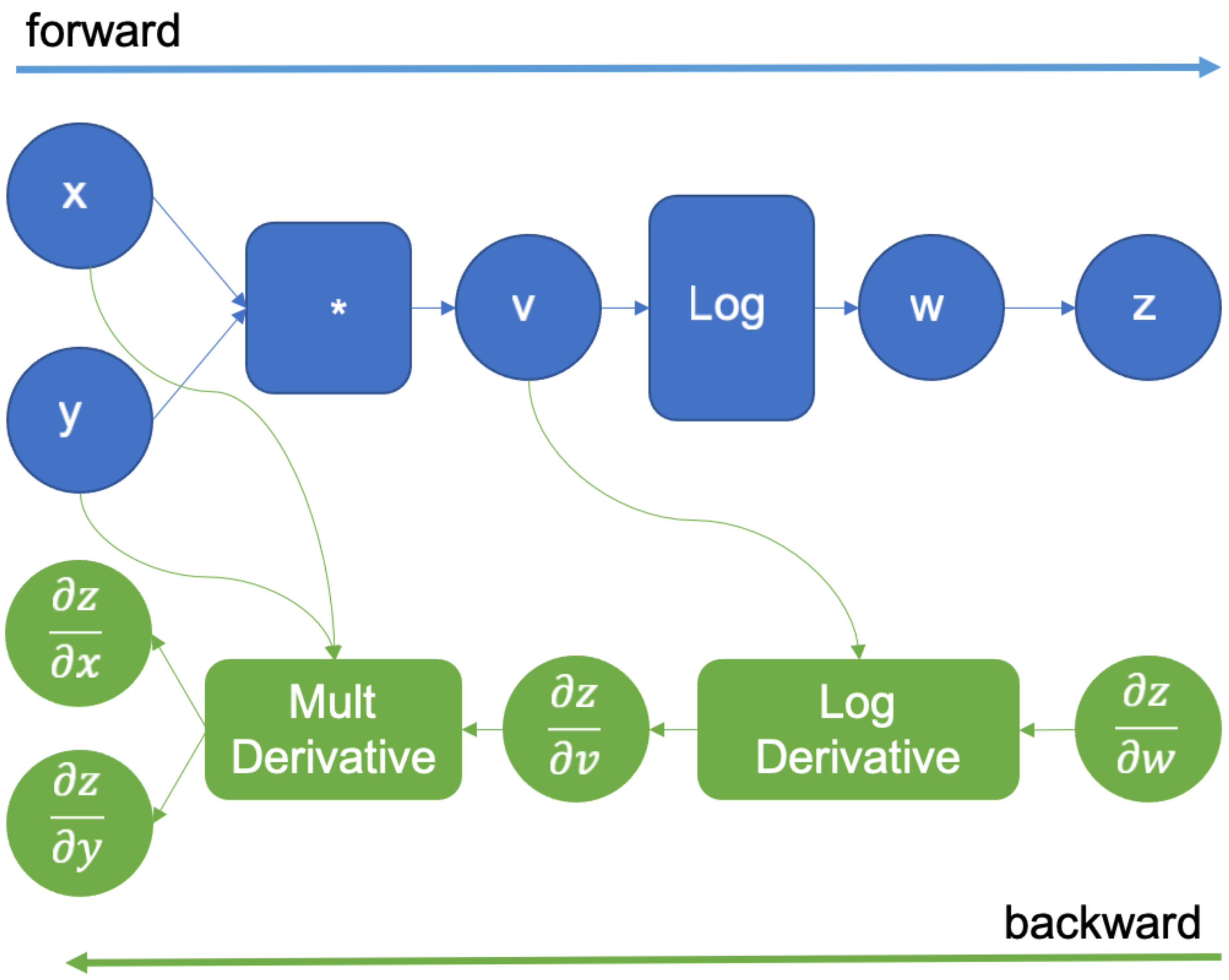


```
traced_cell.save('wrapped_cell.pt')
```

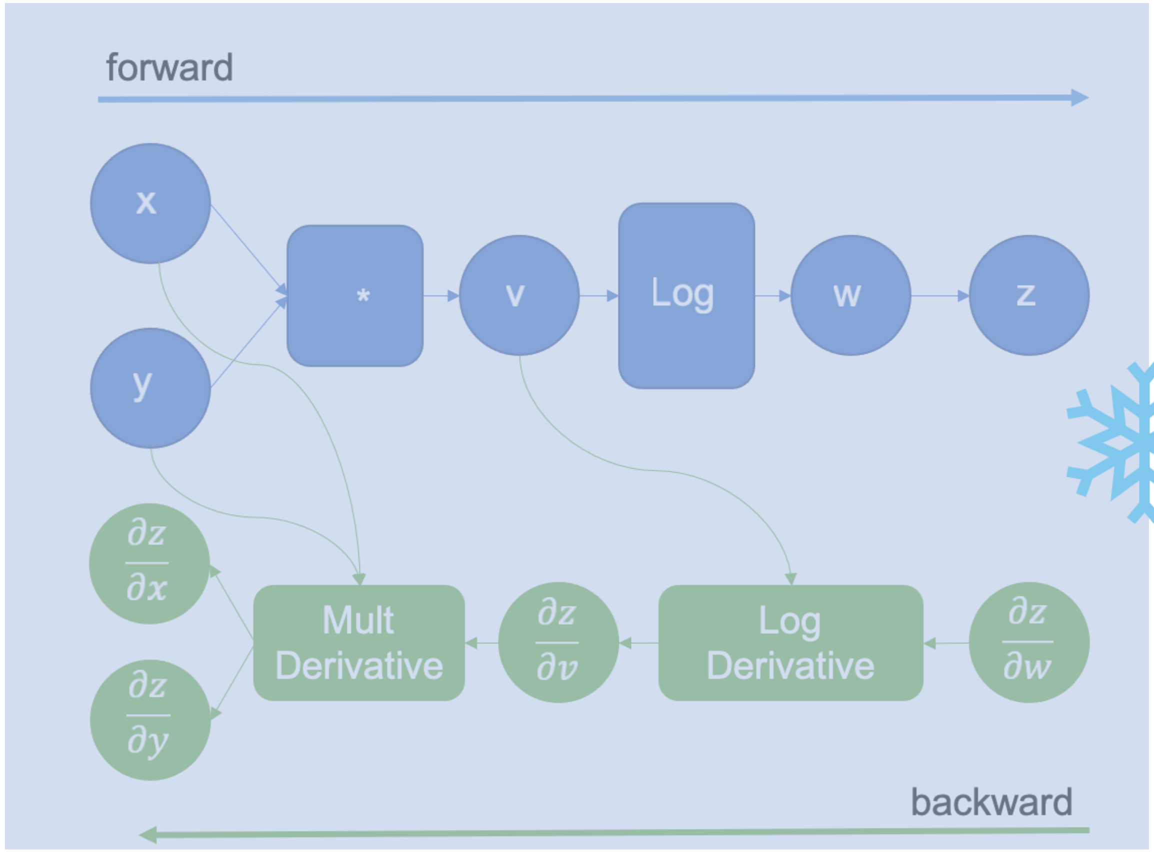
Load in C++

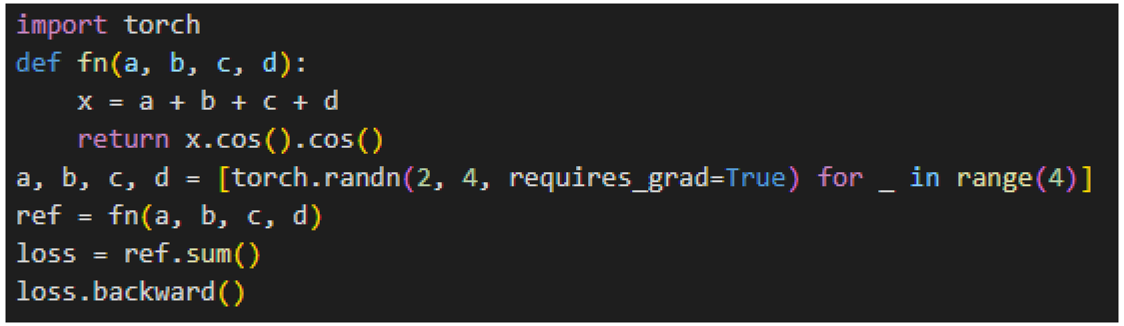


```
#include <torch/script.h>
    ...
    torch::jit::script::Module module;
    ...
    module = torch::jit::load(model_path);
    ...
```

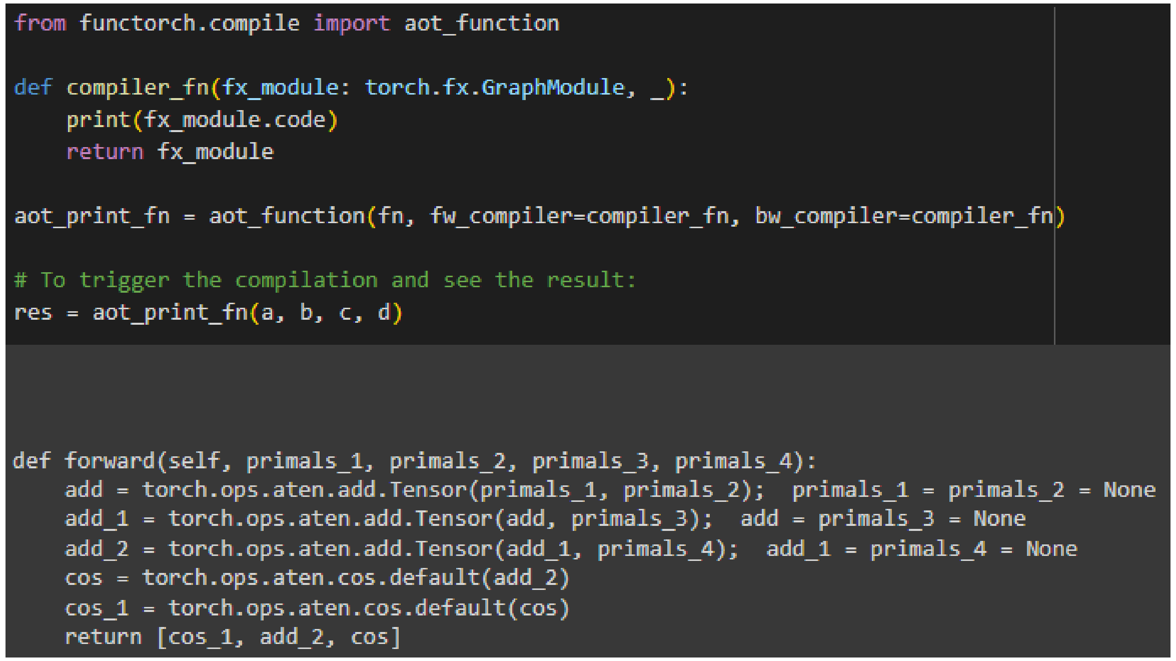

forward
x
y
*
v
Log
w
z
$\frac{\partial z}{\partial x}$
$\frac{\partial z}{\partial y}$
Mult Derivative
$\frac{\partial z}{\partial v}$
Log Derivative
$\frac{\partial z}{\partial w}$
backward

Torch AutoGrad


forward
x
y
*
v
Log
w
z
$\frac{\partial z}{\partial x}$
$\frac{\partial z}{\partial y}$
Mult Derivative
$\frac{\partial z}{\partial v}$
Log Derivative
$\frac{\partial z}{\partial w}$
backward



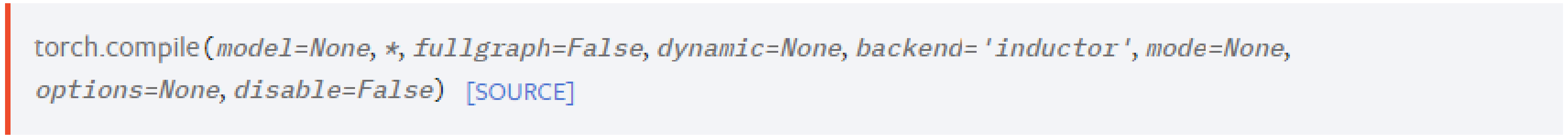
```python
import torch
def fn(a, b, c, d):
    x = a + b + c + d
    return x.cos().cos()
a, b, c, d = [torch.randn(2, 4, requires_grad=True) for _ in range(4)]
ref = fn(a, b, c, d)
loss = ref.sum()
loss.backward()
```



```python
from functorch.compile import aot_function

def compiler_fn(fx_module: torch.fx.GraphModule, _):
    print(fx_module.code)
    return fx_module

aot_print_fn = aot_function(fn, fw_compiler=compiler_fn, bw_compiler=compiler_fn)

# To trigger the compilation and see the result:
res = aot_print_fn(a, b, c, d)
```

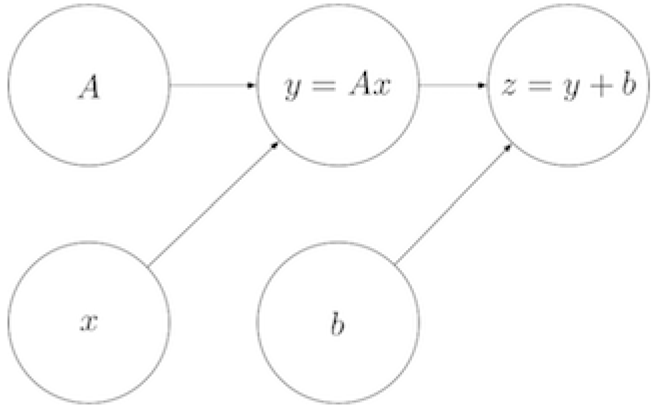
```


def forward(self, primals_1, primals_2, primals_3, primals_4):
    add = torch.ops.aten.add.Tensor(primals_1, primals_2);  primals_1 = primals_2 = None
    add_1 = torch.ops.aten.add.Tensor(add, primals_3);  add = primals_3 = None
    add_2 = torch.ops.aten.add.Tensor(add_1, primals_4);  add_1 = primals_4 = None
    cos = torch.ops.aten.cos.default(add_2)
    cos_1 = torch.ops.aten.cos.default(cos)
    return [cos_1, add_2, cos]
```

Torch Ahead of Time AutoGrad



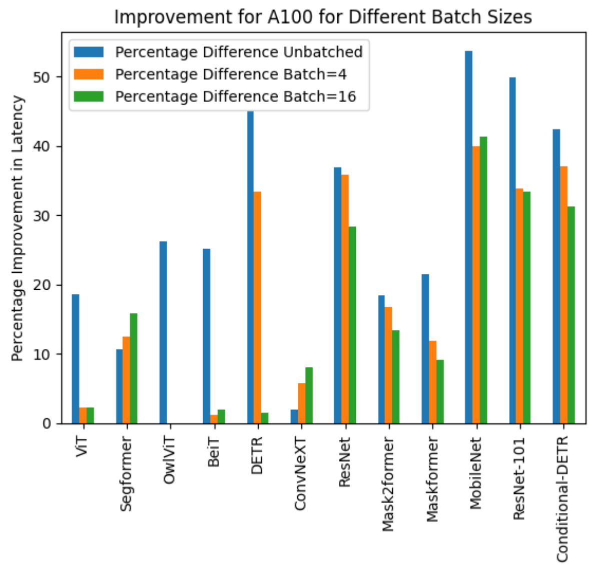
```
torch.compile(model=None, *, fullgraph=False, dynamic=None, backend='inductor', mode=None,
options=None, disable=False) [SOURCE]
```

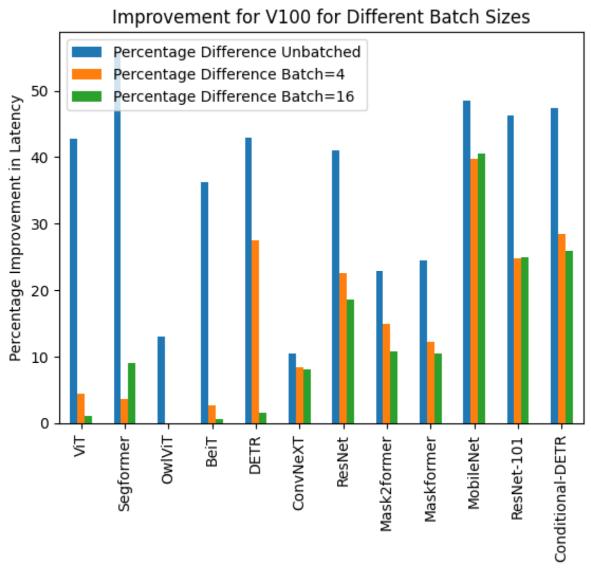
TorchDynamo + AOT AutoGrad + TorchInductor + PrimTorch

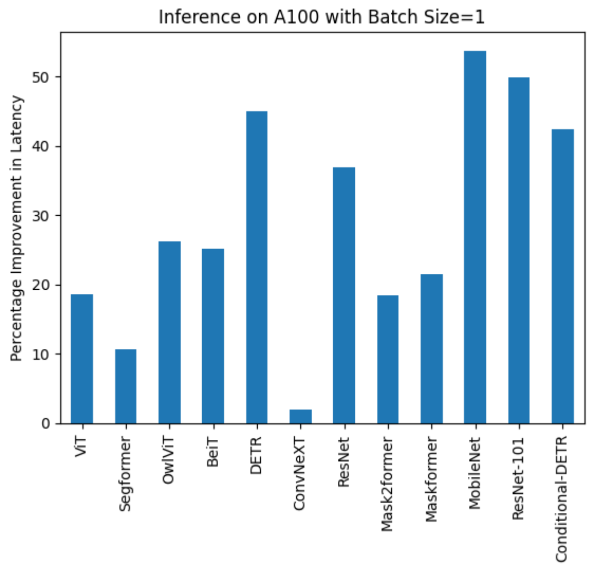


$$\begin{tikzcd}
A \arrow[r] & y = Ax \arrow[r] & z = y + b \\
x \arrow[ur] & b \arrow[ur] &
\end{tikzcd}$$

Torch Compile – Mechanisms







Compilation mode	Initial step time [s]	Initial step memory [MiB]	Training time / iter [ms]	Inference time / iter [ms]
N/A (eager)	1	3675	57	**18**
default	29	3277	34	30
reduce-overhead	29	5736	34	28
max-autotune	35	5736	**32**	30

Torch Compile – Performances

```python
import numpy as np

def kmeans(X, means):
    return np.argmin(np.linalg.norm(X - means[:, None], axis=2), axis=0)

npts = 10_000_000
X = np.repeat([[5, 5], [10, 10]], [npts, npts], axis=0)
X = X + np.random.randn(*X.shape)  # 2 distinct "blobs"
means = np.array([[5, 5], [10, 10]])
np_pred = kmeans(X, means)
```

Torch Compile Wrapping

```python
import torch

compiled_fn = torch.compile(kmeans)
compiled_pred = compiled_fn(X, means)
assert np.allclose(np_pred, compiled_pred)
```

Torch Compile Performance

```python
print(f"Non-compiled average time: {non_compiled_time:.6f} seconds")
print(f"Compiled average time: {compiled_time:.6f} seconds")
```

```
Non-compiled average time: 2.521456 seconds
Compiled average time: 0.233836 seconds
```

Torch Compile - numpy

NumPy

RAPIDS

Accelerated with NVIDIA

CuPy

« Numpy » on gpus