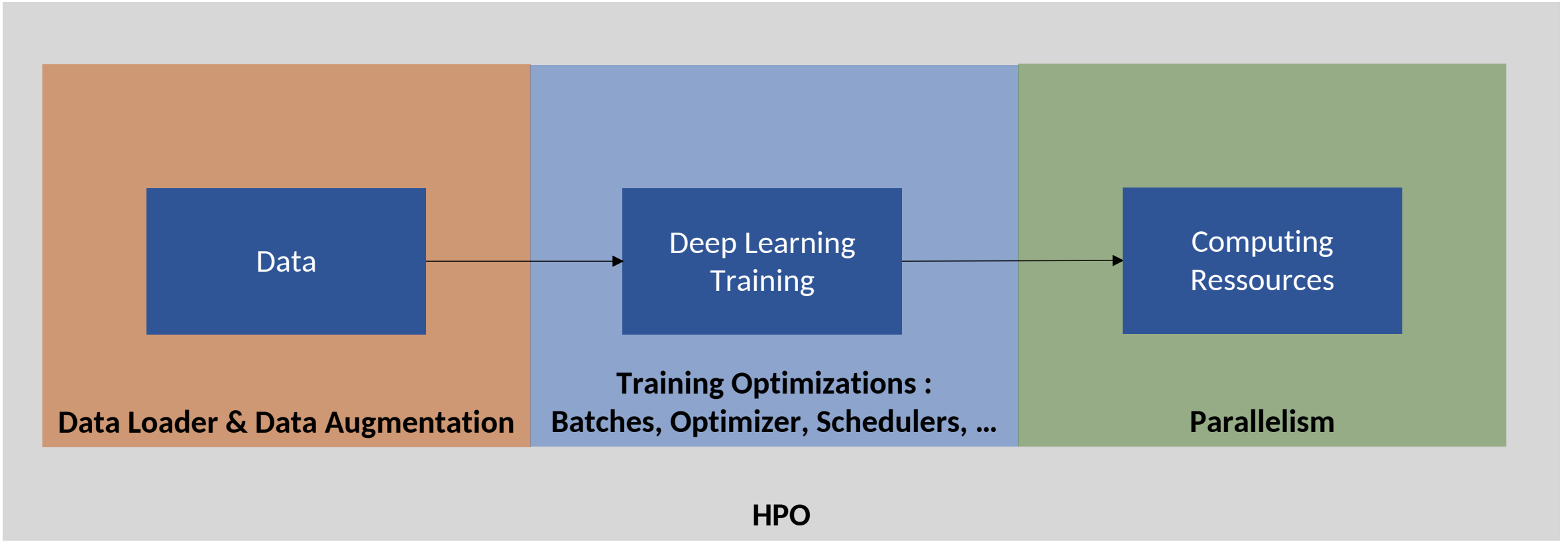
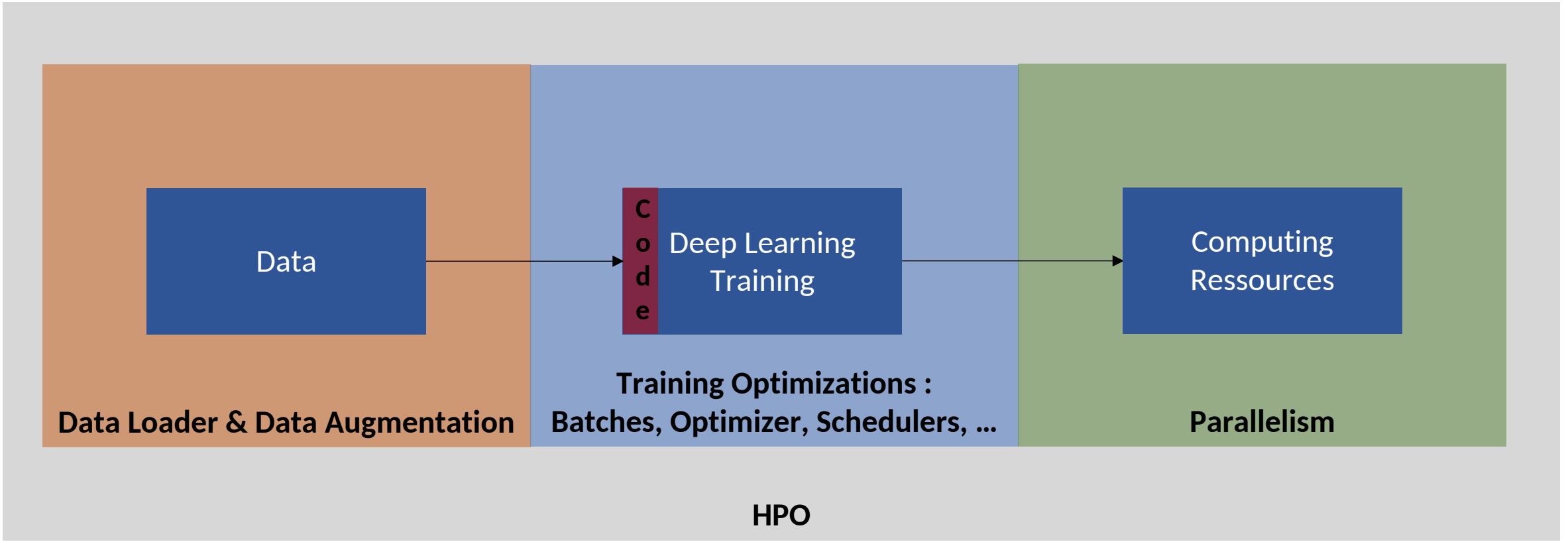
Optimised Deep Learning on Jean Zay (DLO-JZ)

Torch & Compilation

INSTITUT DU DÉVELOPPEMENT ET DES RESSOURCES EN INFORMATIQUE SCIENTIFIQUE



Optimize everything ?



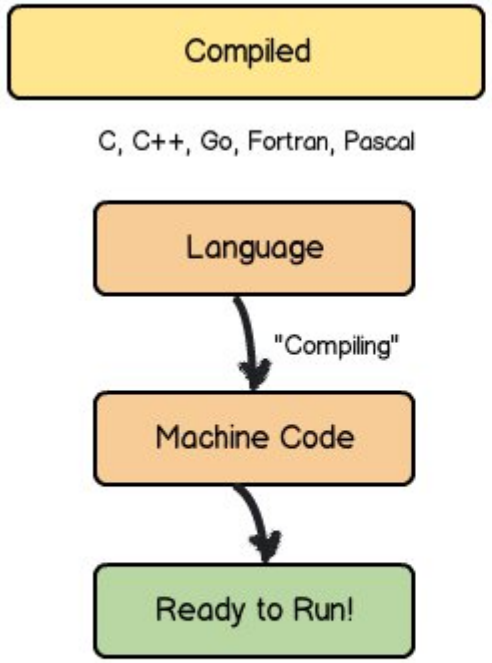
Optimize everything !

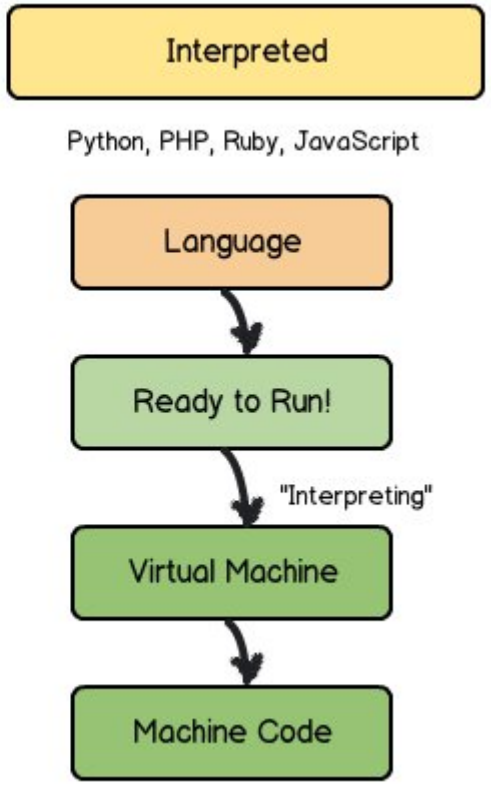
helloworld.c

```c
#include <stdio.h>

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

    return 0;
}
```

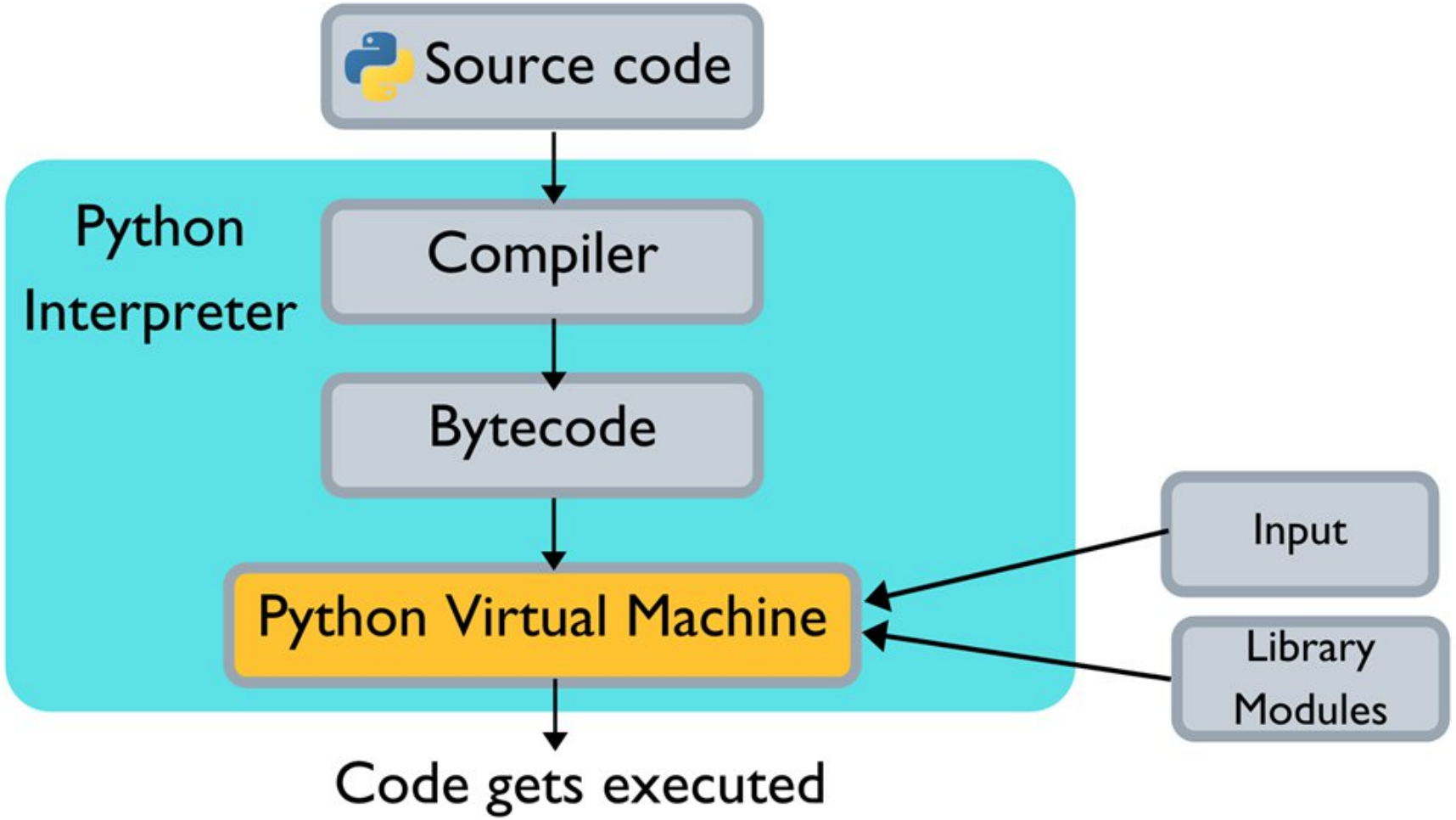
hello.py

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

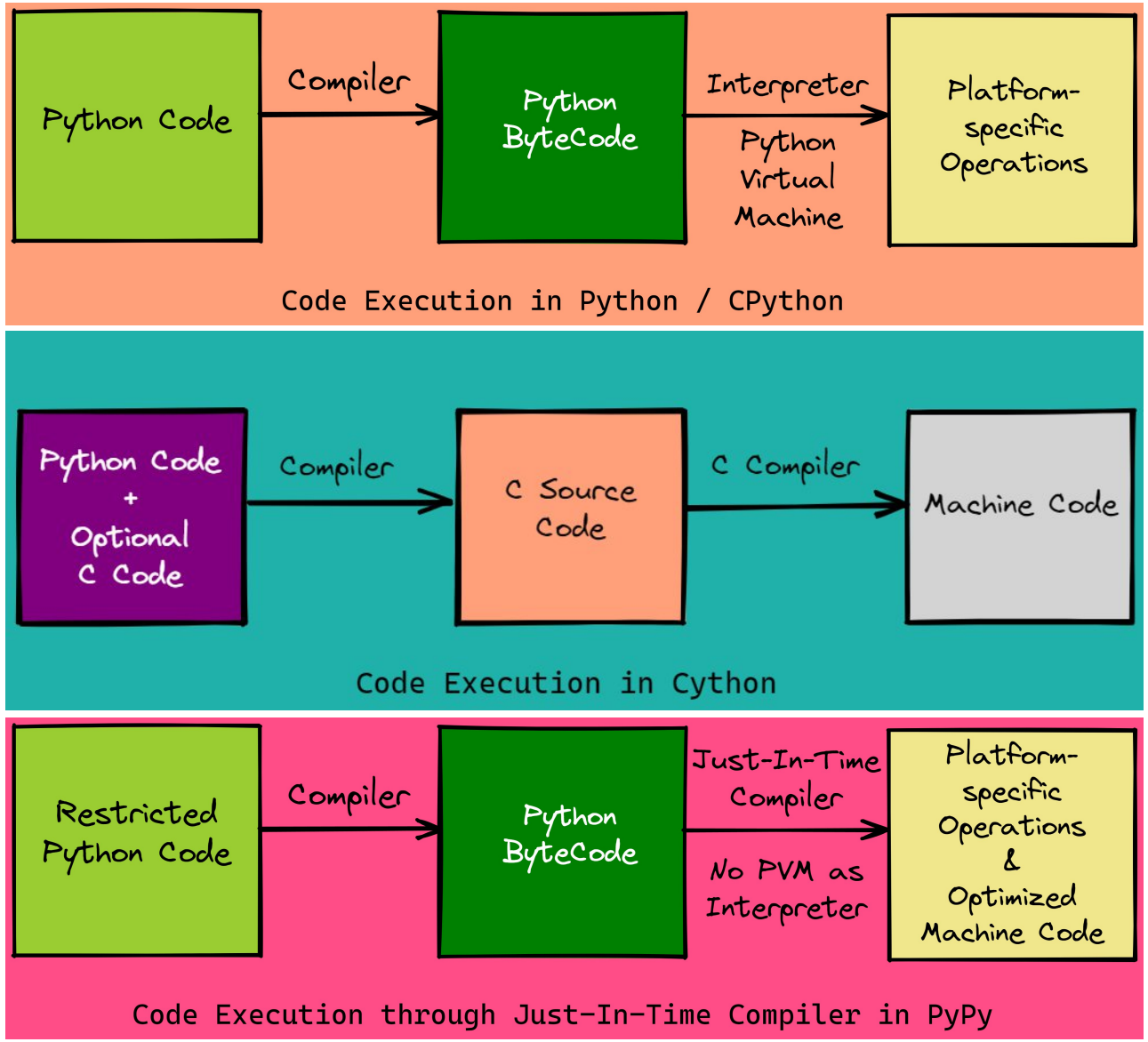




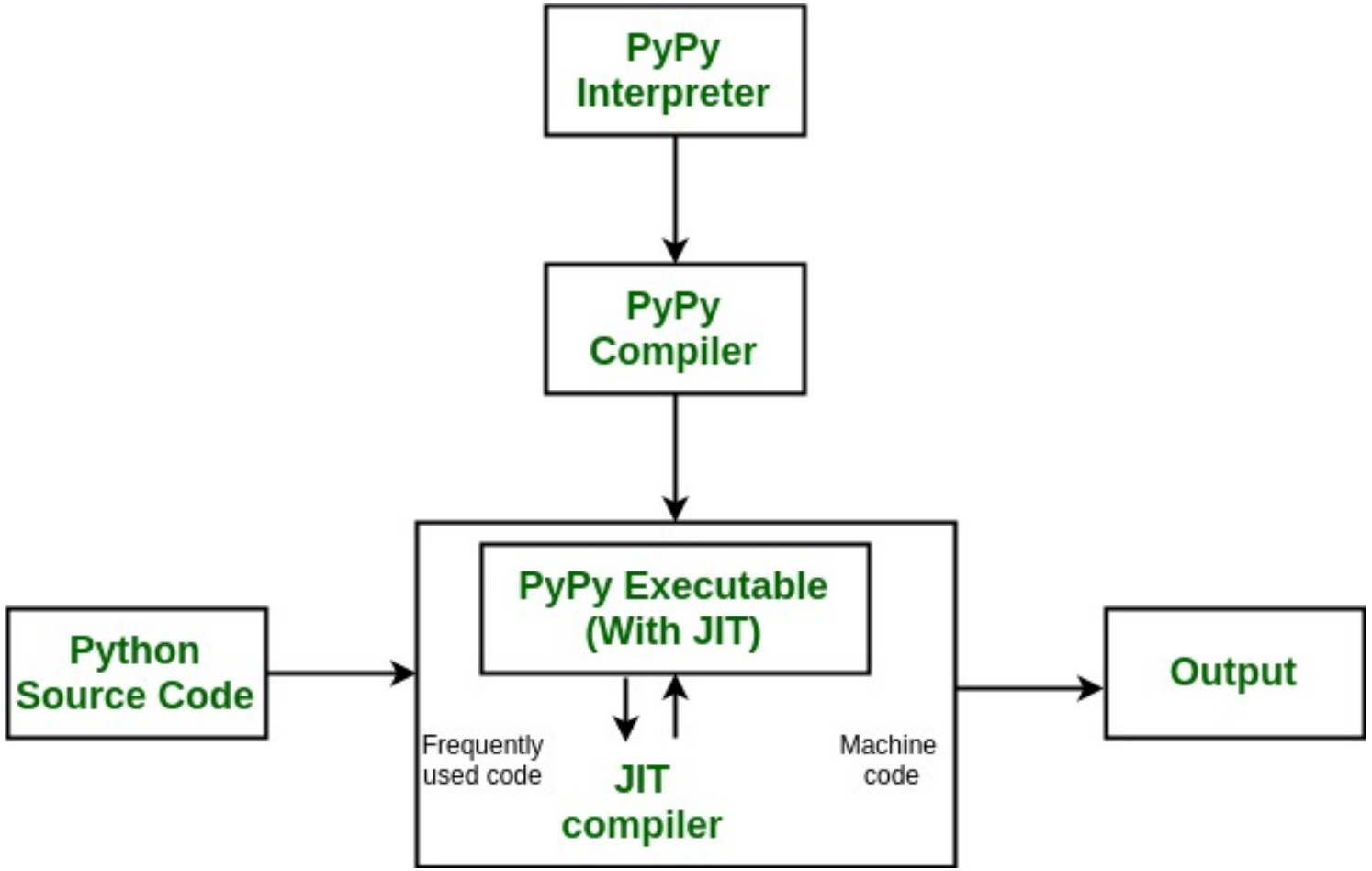
Code?



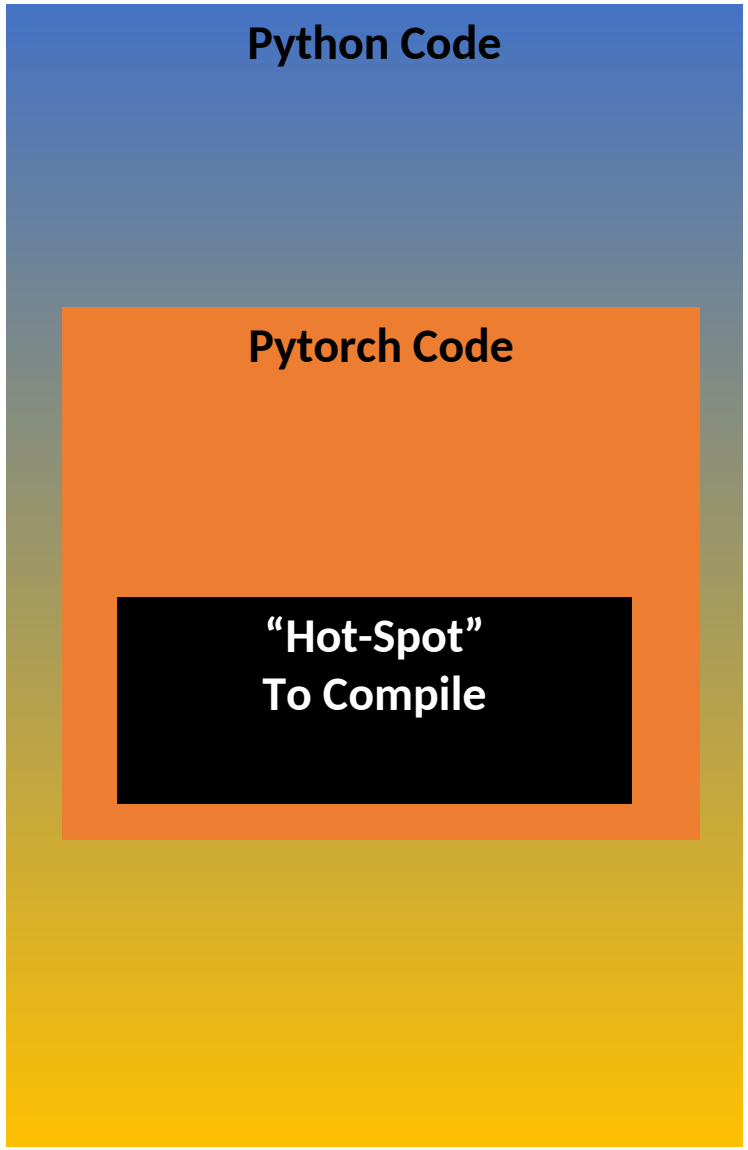
Python ? CPython !



Cpython, Jython, Cython, PyPy



Just-In-Time Compilation



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

Scripting

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

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

TorchScript – Scripting

```
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 – Performance

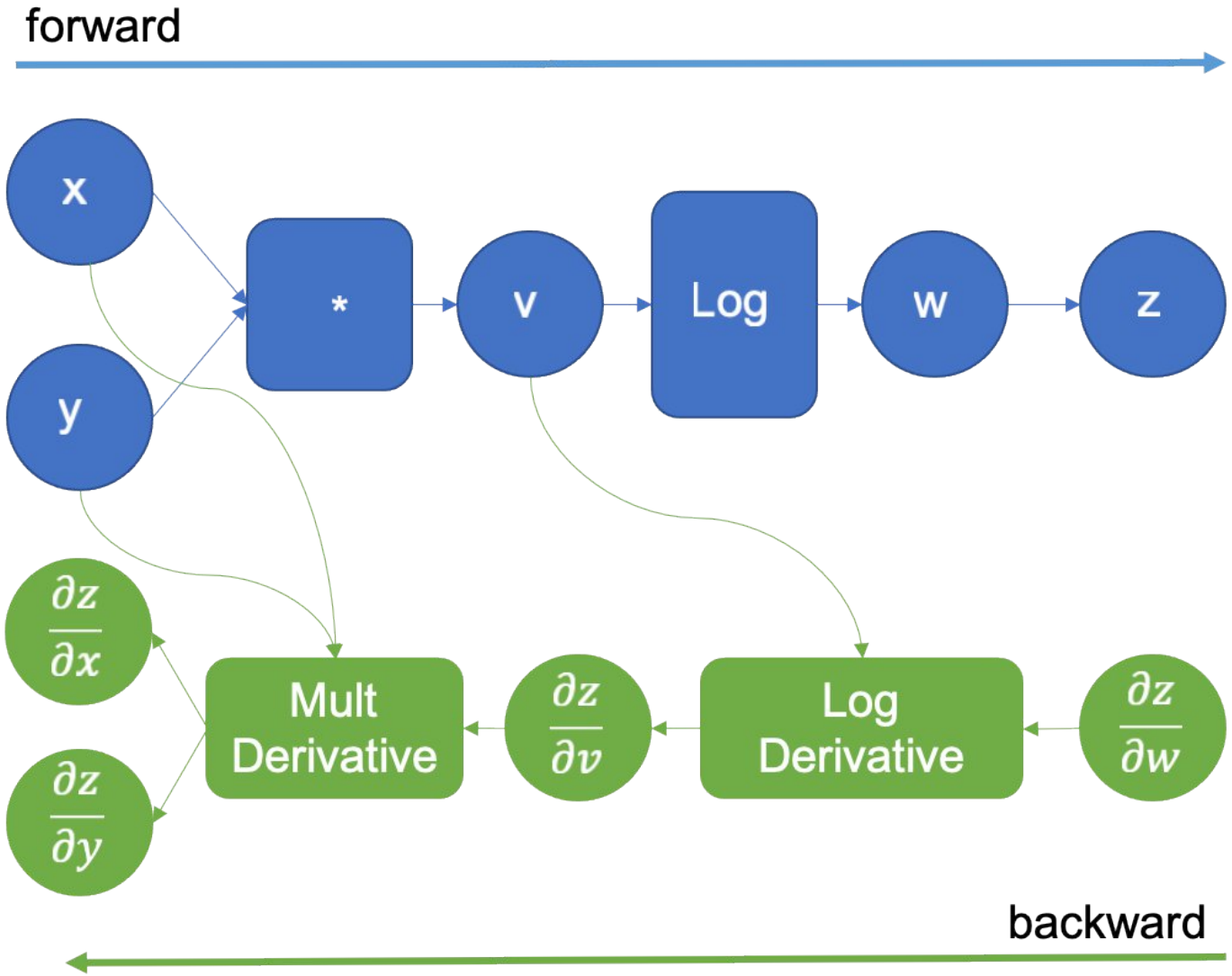
Save in Python

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

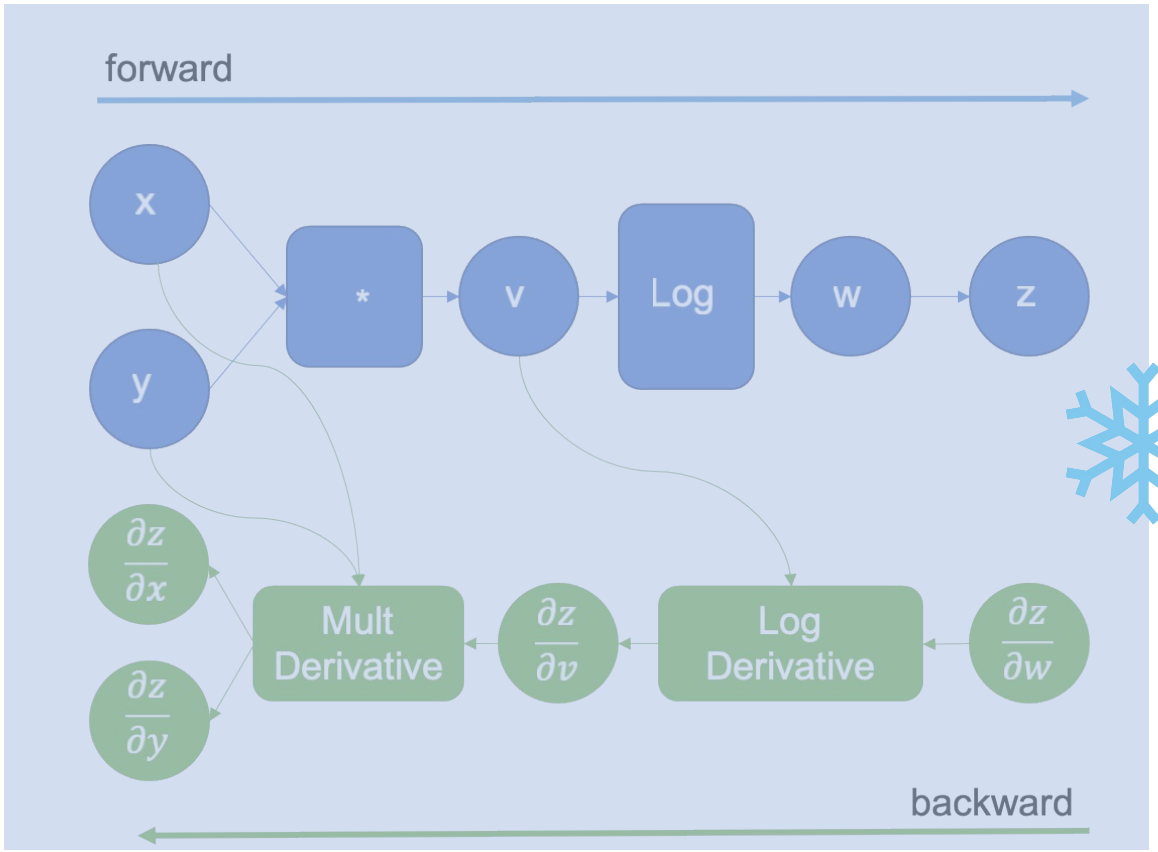
Load in C++

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

TorchScript – Save & Load



Torch AutoGrad




```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()
```

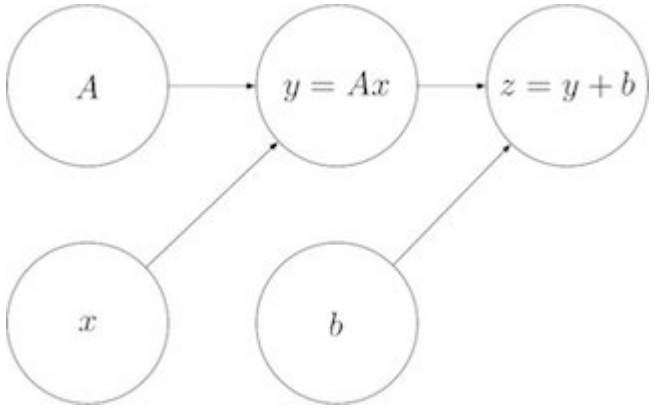
```python
from functorch.compile import aot_function

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)
```

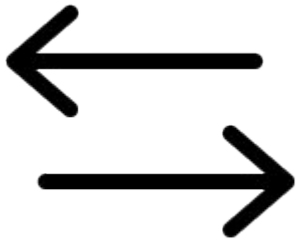
```python
def forward(self, primals_1, primals_2, primals_3, primals_4):
    add = torch.ops.aten.add.Tensor(primals_1, primals_2);  primals_1 = primals_2 = None
    add_1 = torch.ops.aten.add.Tensor(add, primals_3);  add = primals_3 = None
    add_2 = torch.ops.aten.add.Tensor(add_1, primals_4);  add_1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

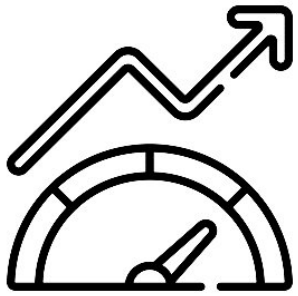
Torch Ahead of Time AutoGrad

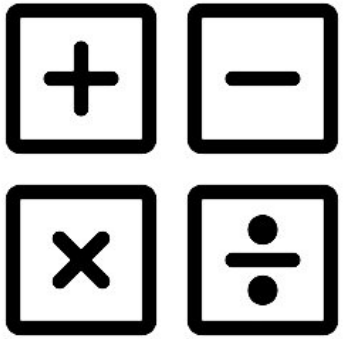
```
torch.compile(model=None, *, fullgraph=False, dynamic=None, backend='inductor', mode=None,
options=None, disable=False) [SOURCE]
```

TorchDynamo + AOT AutoGrad + TorchInductor + PrimTorch

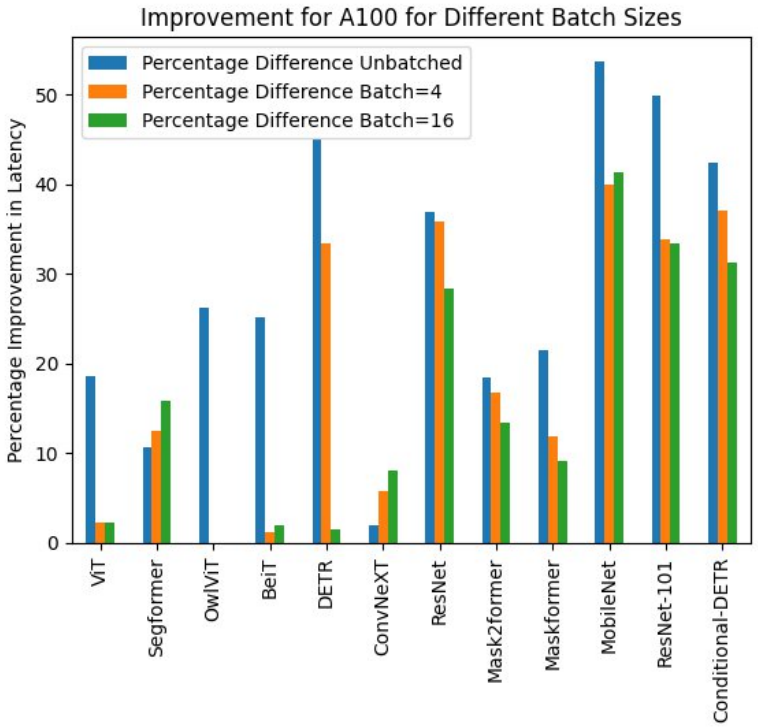


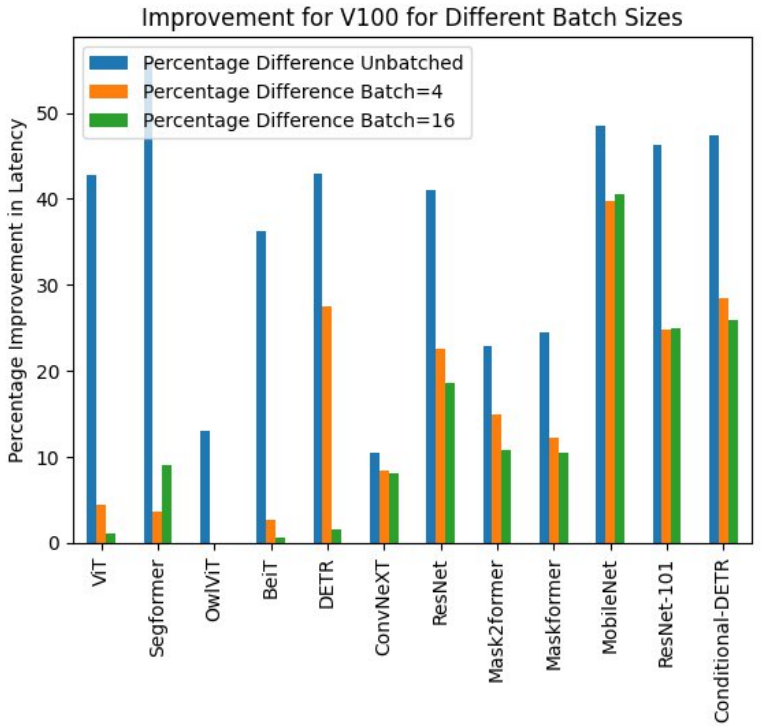


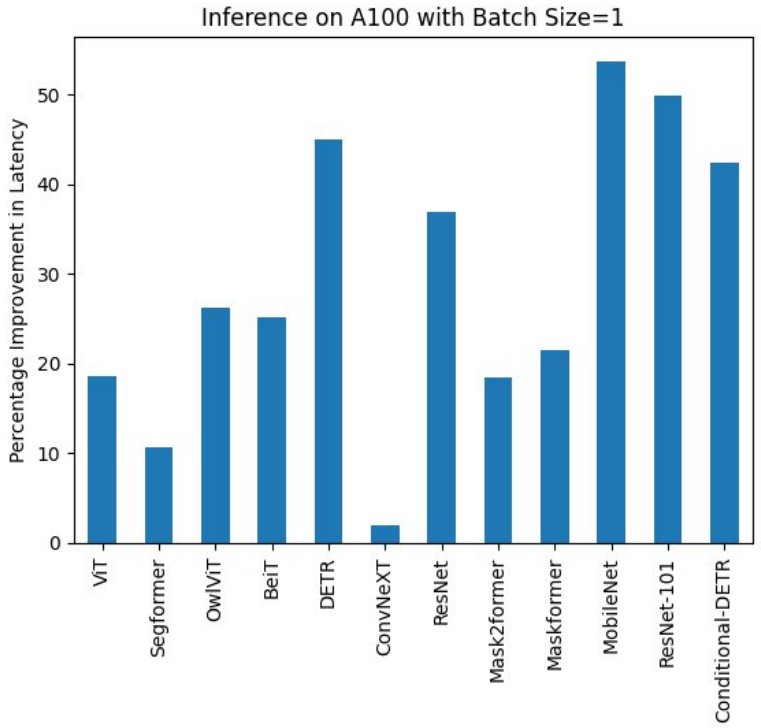




Torch Compile – Mechanisms







Torch Compile – Performances

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

RAPIDS

Accelerated with

NVIDIA.

« Numpy » on gpus

Flax Linen

Neural networks with JAX

Flax Linen delivers an **end-to-end and flexible user experience for researchers who use JAX with neural networks**. Flax exposes the full power of JAX. It is made up of loosely coupled libraries, which are showcased with end-to-end integrated guides and examples.

jax.jit

```
jax.jit(fun, in_shardings=UnspecifiedValue, out_shardings=UnspecifiedValue,
static_argnums=None, static_argnames=None, donate_argnums=None, donate_argnames=None,
keep_unused=False, device=None, backend=None, inline=False, abstracted_axes=None)
```

Sets up `fun` for just-in-time compilation with XLA. [source]

GPU memory allocation

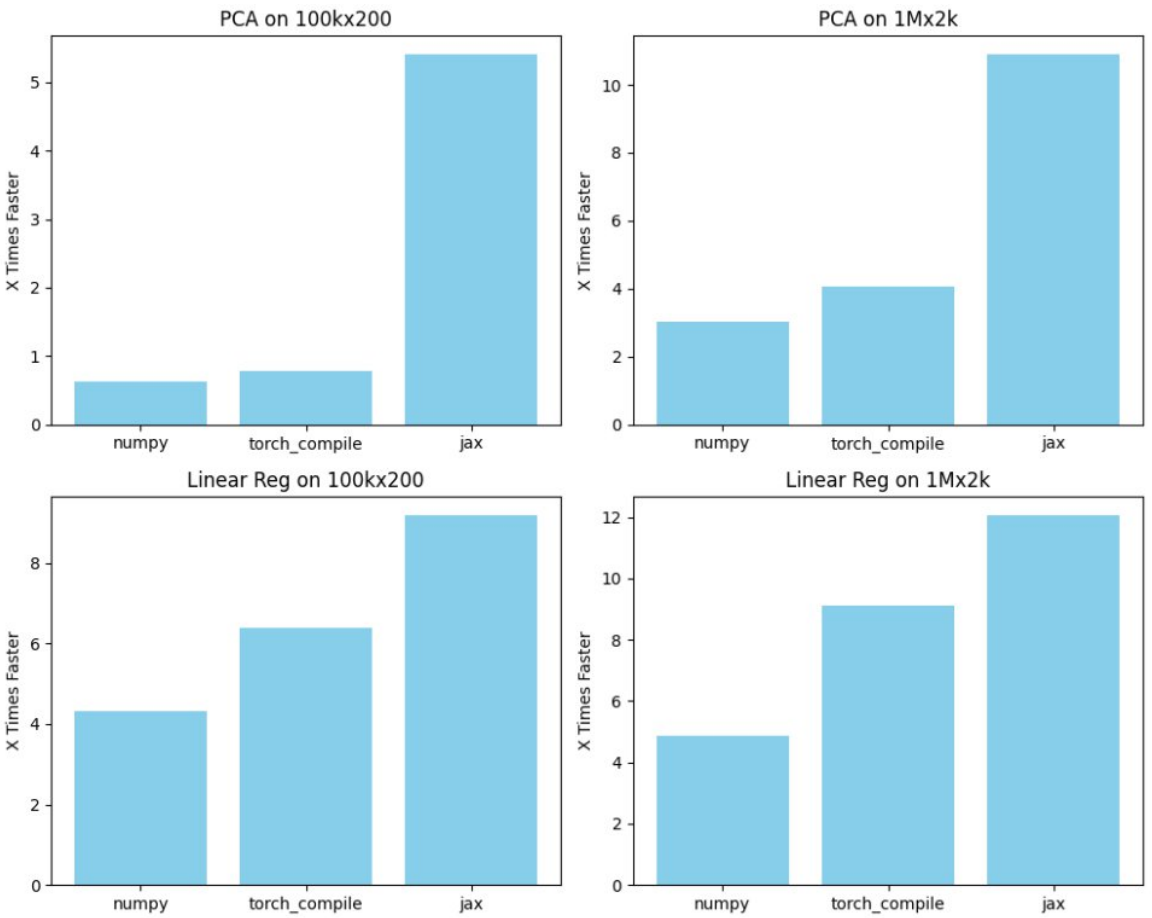
JAX will preallocate 75% of the total GPU memory when the first JAX operation is run. Preallocating minimizes allocation overhead and memory fragmentation, but can sometimes cause out-of-memory (OOM) errors. If your JAX process fails with OOM, the following environment variables can be used to override the default behavior:

`XLA_PYTHON_CLIENT_PREALLOCATE=false`

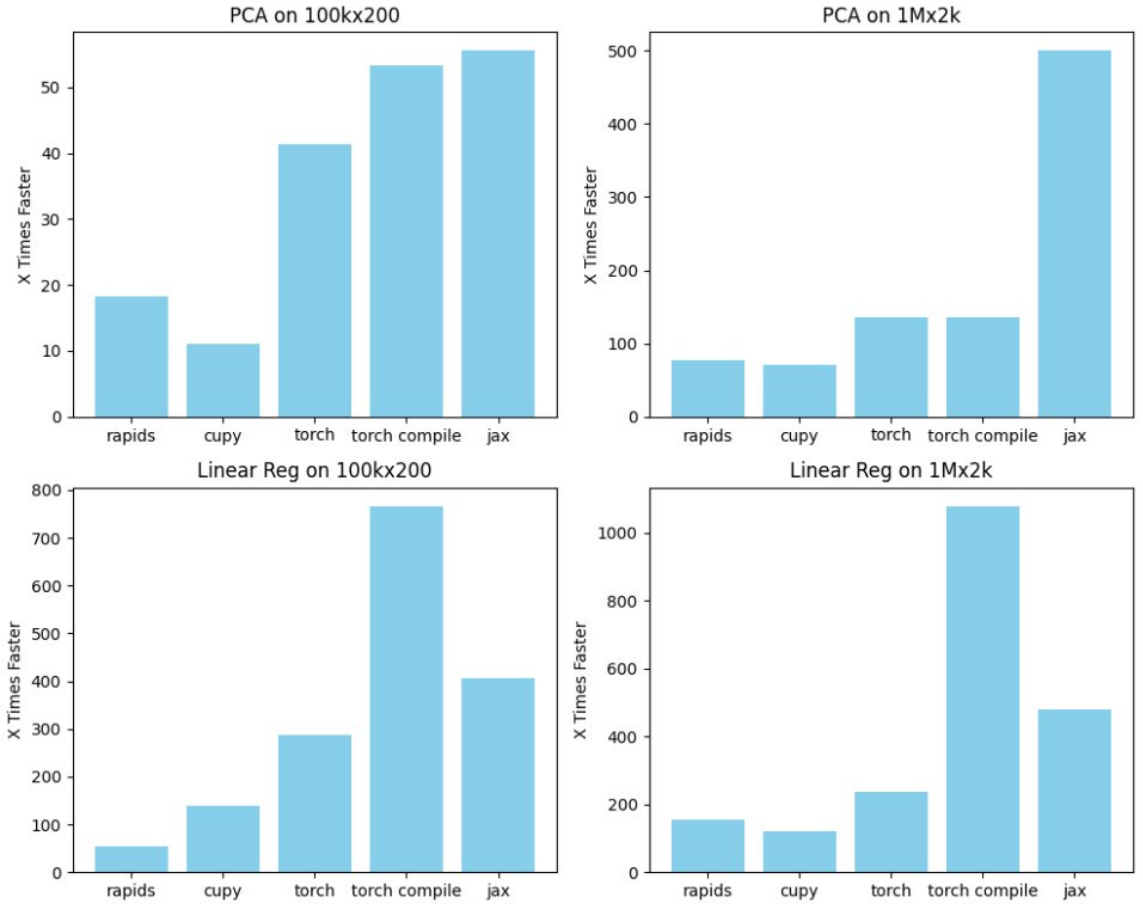
This disables the preallocation behavior. JAX will instead allocate GPU memory as needed, potentially decreasing the overall memory usage. However, this behavior is more prone to GPU memory fragmentation, meaning a JAX program that uses most of the available GPU memory may OOM with preallocation disabled.

JAX tips

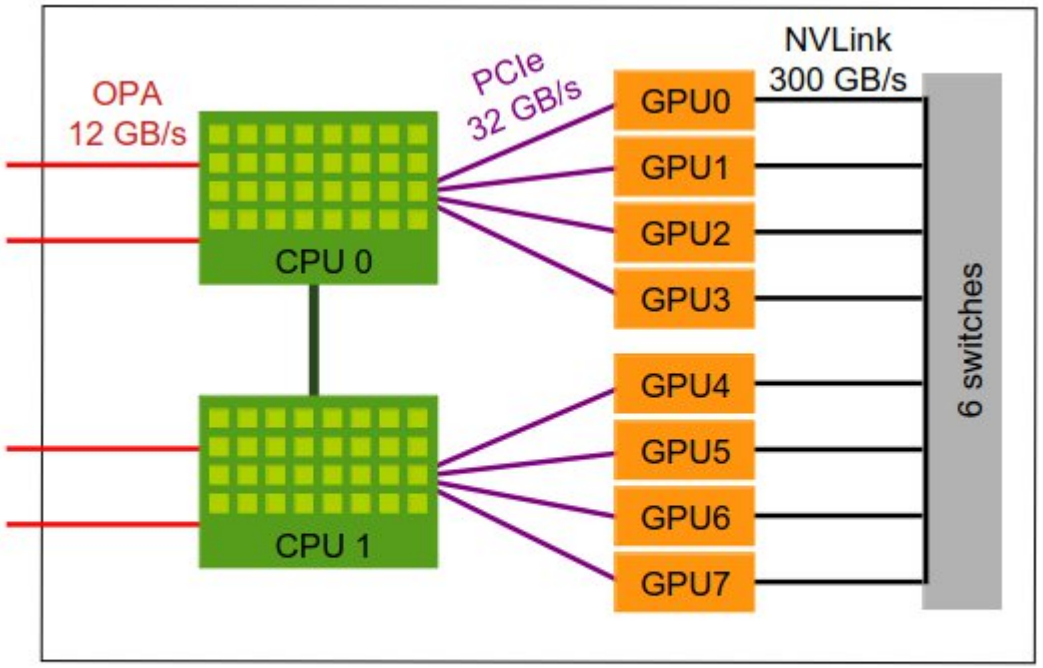
On CPU



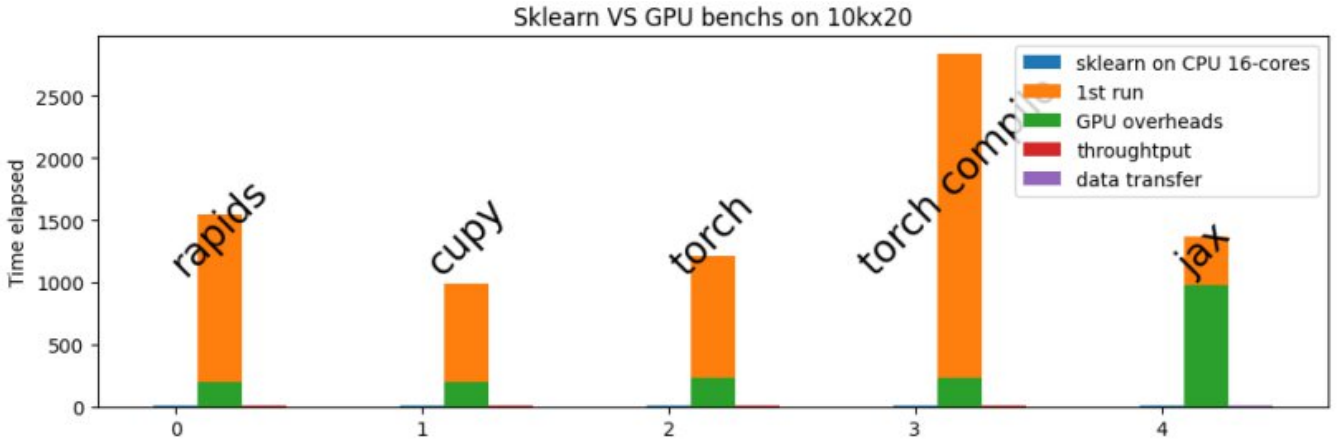
On GPU

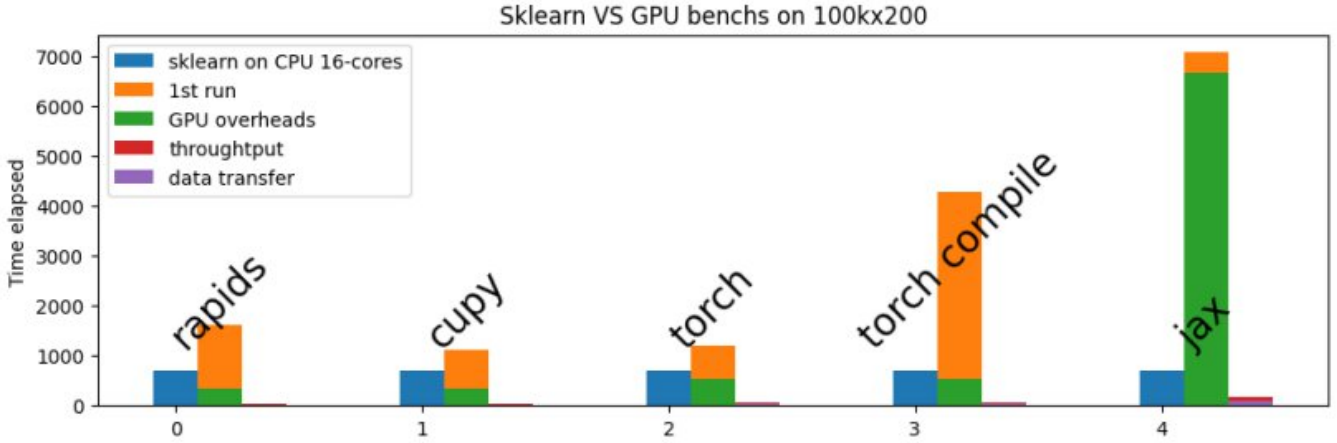


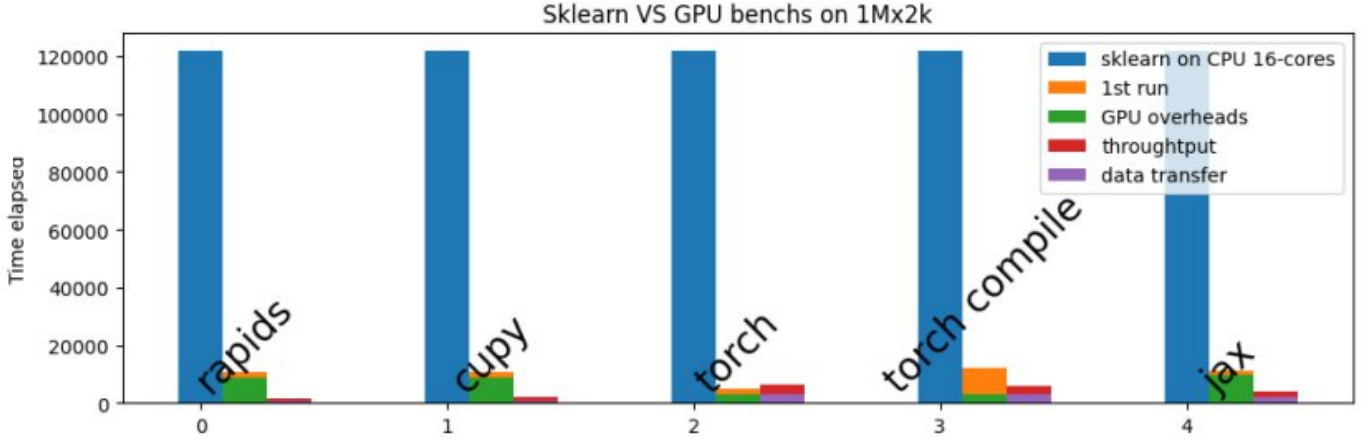
Machine Learning speed up



Node 8 × A100 80Go







Really worth it ?