FROM RESEARCH TO PRODUCTION WITH PYTORCH 1.0

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I've been using PyTorch a few months now and I've never felt better. I have more energy. My skin is clearer. My eye sight has improved.

11:56 AM - 26 May 2017

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WHAT IS PYTORCH?

DYNAMIC NEURAL NETWORKS WITH STRONG GPU ACCELERATION

A MACHINE LEARNING FRAMEWORK BORN WITH AN EMPHASIS ON

EAGER EXECUTION

DYNAMIC NEURAL NETWORKS

GPU ACCELERATION

DISTRIBUTED TRAINING

SIMPLICITY OVER COMPLEXITY

MISSION

PyTorch enables . . .

MISSION

PyTorch enables . . .

Research

252 Mentions @ ICLR 2018
(87 in 2018)

MISSION

PyTorch enables . . .

Research

Ecosystems

HOROVOD

AllenNLP

MISSION

PyTorch enables . . .

Research

Ecosystems

ELF

Translate

Glow

MISSION

PyTorch enables . . .

Research

Ecosystems

Partnerships

A MACHINE LEARNING FRAMEWORK BORN WITH AN EMPHASIS ON

- EAGER EXECUTION
- DYNAMIC NEURAL NETWORKS
- GPU ACCELERATION
- DISTRIBUTED TRAINING
- SIMPLICITY OVER COMPLEXITY

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EAGER EXECUTION

DYNAMIC NEURAL NETWORKS

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DISTRIBUTED TRAINING

SIMPLICITY OVER COMPLEXITY

EAGER

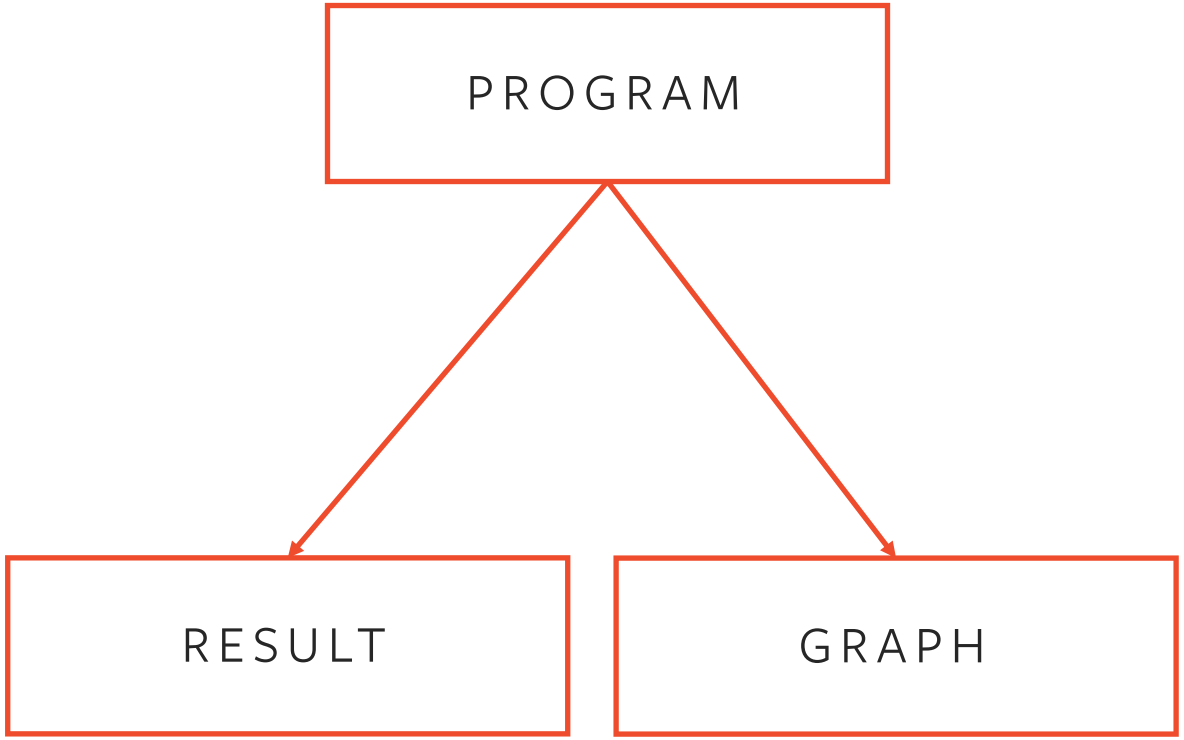
STATIC

```
Matrix a = ...;
Matrix b = ...;
Matrix c = ...;
scalar s = 7;

d = s * a + b;
e = matmul(c, d);

if s > 0  {
    x = d;
} else {
    x = e;
}

while s > 0  {
    x = input();
    c = matmul(c, x);
}

result = c;
```

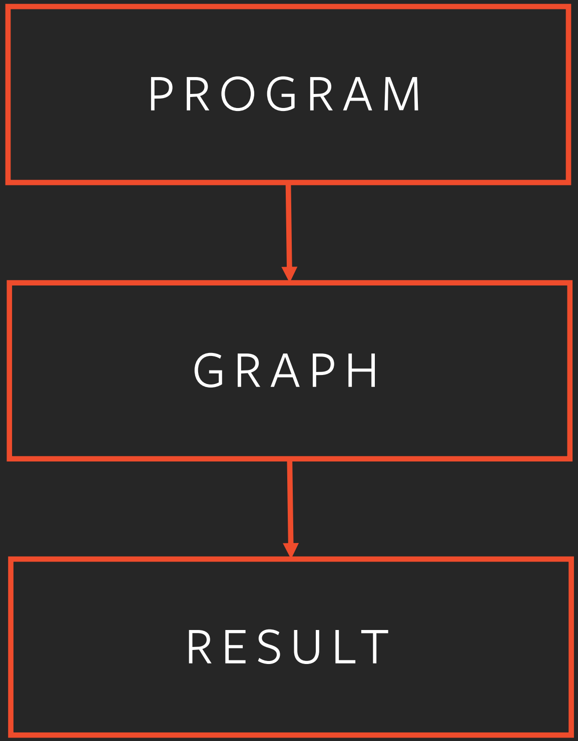
EAGER

```
Matrix<6, 9> a = ...;
Matrix<6, 9> b = ...;
Matrix<16, 6> c = ...;
scalar s = 7;

d = s * a + b;
e = matmul(c, d);

x = if_clause(s > 0, d, e);

while_loop(s > 0, [x, c], lambda x,c {
    x = input();
    c = matmul(c, x);
});

result = evaluate(x);
```

STATIC



EAGER



STATIC

EAGER

STATIC

PRO

— No boundaries on flexibility
— Happier debugging
— No expensive compilation

CONTRA

— Harder to optimize
— Harder to deploy

EAGER

STATIC

EAGER

PRO

- No boundaries on flexibility
- Happier debugging
- No expensive compilation

CONTRA

- Harder to optimize
- Harder to deploy

STATIC

PRO

- Easier to optimize
- Easier to deploy
- Easier to post-process

CONTRA

- Harder to understand
- Harder to debug
- Less flexible

PYTORCH 1.0

A SEAMLESS PATH FROM RESEARCH TO PRODUCTION WITH TORCH SCRIPT

PyTorch

Models are Python programs

- Intuitive, Native
- Debuggable — `print` and `pdb`
- Hackable — use any Python library

PyTorch

Models are Python programs

- Simple
- Debuggable — `print` and `pdb`
- Hackable — use any Python library

- Needs Python to run
- Difficult to optimize and parallelize

PyTorch *Eager Mode*

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PyTorch *Eager Mode*

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PyTorch *Script Mode*

Models are programs written in an optimizable subset of Python

- Production deployment
- No Python dependency
- Optimizable

PYTORCH JIT

Tools to transition eager code into script mode

EAGER MODE

For prototyping, training, and experiments

`@torch.jit.script`

`torch.jit.trace`

SCRIPT MODE

For use at scale in production

Transitioning a model with `torch.jit.trace`

Take an existing eager model, and provide example inputs.

The tracer runs the function, recording the tensor operations performed.

We turn the recording into a Torch Script module.

- Can reuse existing eager model code
- ⚠️ Control-flow is ignored

```
import torch
import torchvision


def foo(x, y):
  return 2*x + y


# trace a model by providing example inputs
traced_foo = torch.jit.trace(foo,
                             (torch.rand(3), torch.rand(3)))


traced_resnet = torch.jit.trace(torchvision.models.resnet18(),
                                torch.rand(1, 3, 224, 224))
```

Transitioning a model with `@torch.jit.script`

Write model directly in a subset of Python, annotated with @torch.jit.script or @torch.jit.scri

- Control-flow is pre
- `print` statement debugging
- Remove the annot standard Python tools.

```
class RNN(torch.jit.ScriptModule):
  def __init__(self, W_h, U_h, W_y, b_h, b_y):

  def forward(self, x, h):
    y = []
    for t in range(x.size(0)):
      h = torch.tanh(x[t] @ self.W_h + h @ self.U_h + self.b_h)
      y += [torch.tanh(h @ self.W_y + self.b_y)]
      if t % 10 == 0:
        print("stats: ", h.mean(), h.var())
    return torch.stack(y), h
```

You can mix both trace and script in a single model.

Loading a model without Python

Torch Script models can be saved to a model archive, and loaded in a python-free executable using a C++ API.

Our C++ Tensor API is the same as our Python API, so you can do preprocessing and post processing before calling the model.

```
# Python: save model
traced_resnet = torch.jit.trace(torchvision.models.resnet18(),
                                torch.rand(1, 3, 224, 224))
traced_resnet.save("serialized_resnet.pt")
```

```
// C++: load and run model
auto module = torch::jit::load("serialized_resnet.pt");
auto example = torch::rand({1, 3, 224, 224});
auto output = module->forward({example}).toTensor();
std::cout << output.slice(1, 0, 5) << '\n';
```

What subset of PyTorch is valid Torch Script?

- ✓ Tensors and numeric primitives
- ✓ If statements
- ✓ Simple loops
- ✓ Code organization using `nn.Module`
- ✓ Tuples, Lists
- ✓ `print` and strings
- ✓ Gradients propagation through script functions

- ✗ In-place updates to tensors or lists
- ✗ Direct use of standard `nn.Modules` like `nn.Conv` (trace them instead!)
- ✗ Calling `grad()` or `backwards()` within `@script`

Coming in 1.0 stable

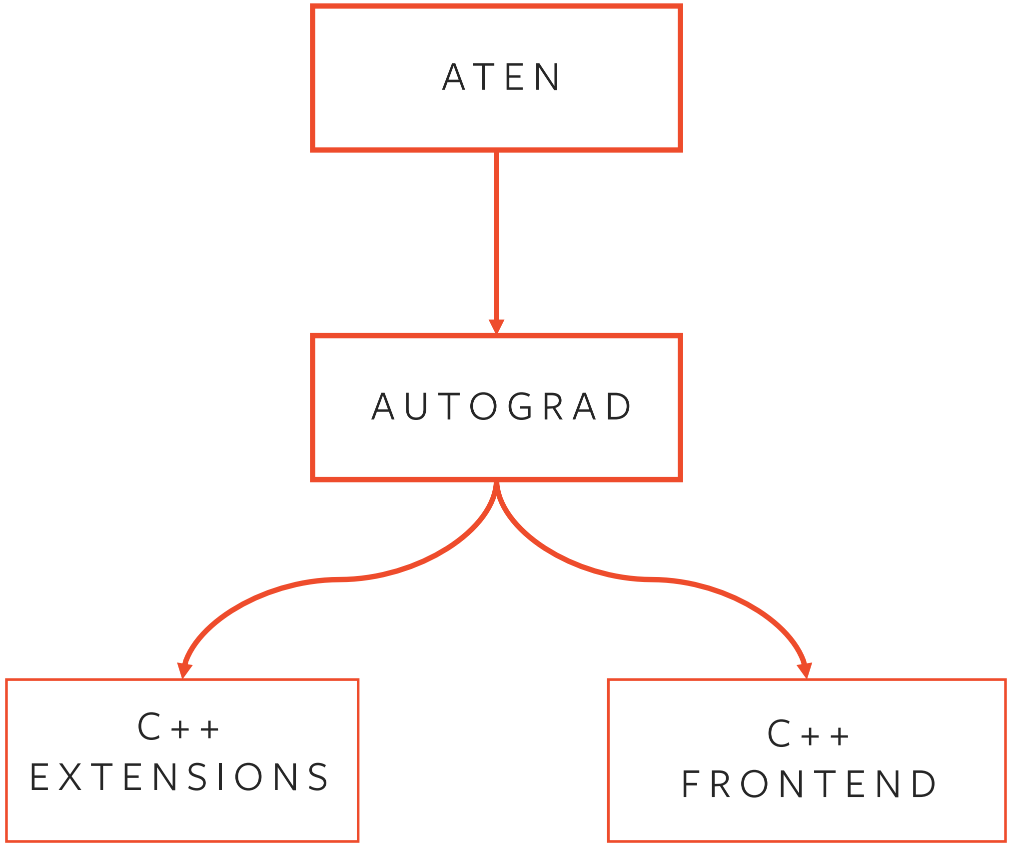
For more details https://pytorch.org/docs/master/jit.html#torch-script-language-reference

PYTORCH IN C++

FLEXIBILITY
SIMPLICITY
PERFORMANCE
ACROSS LANGUAGE BOUNDARIES

ENABLING PATHWAYS

RESEARCH	PRODUCTION
EAGER	SCRIPT
PYTHON	C++



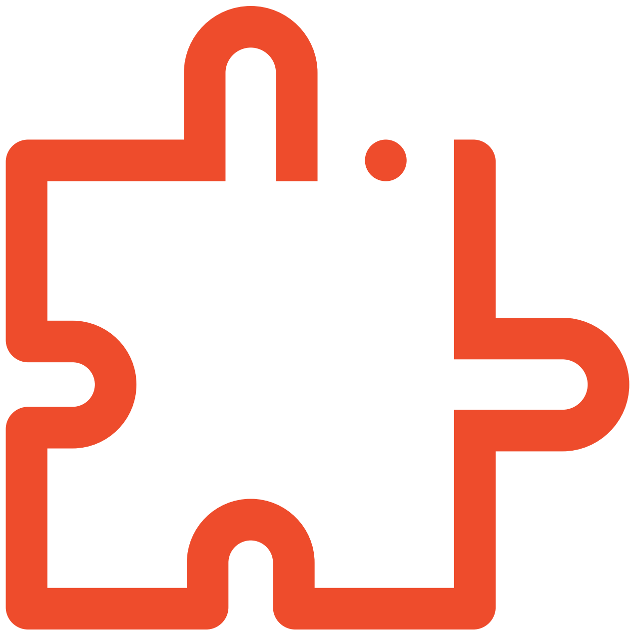
PYTORCH C++ API

```
#include <torch/csrc/autograd/variable.h>
#include <torch/csrc/autograd/function.h>

at::Tensor x =
  torch::ones({2, 3}, torch::requires_grad());
at::Tensor y = torch::randn({2, 3});
auto z = x + y;

z.backward();
std::cout << x.grad();
```

```
#include <ATen/ATen.h>
at::Tensor x = at::ones({2, 3});
at::Tensor y = at::randn({2, 3});
auto z = x + y;
z.mul_(2);
```

C++ EXTENSIONS

The power of C++, CUDA and ATen
in imperative PyTorch models



```cpp
#include <torch/extension.h>
#include <opencv2/opencv.hpp>

at::Tensor compute(at::Tensor x, at::Tensor w) {
  cv::Mat input(x.size(0), x.size(1), CV_32FC1, x.data<float>());
  cv::Mat warp(3, 3, CV_32FC1, w.data<float>());

  cv::Mat output;
  cv::warpPerspective(input, output, warp, {64, 64});

  return torch::from_blob(output.ptr<float>(), {64, 64}).clone();
}

PYBIND11_MODULE(TORCH_EXTENSION_NAME, m) {
  m.def("compute", &compute);
}
```

C++ EXTENSION

```python
from setuptools import setup
from torch.utils.cpp_extension \
    import BuildExtension, CppExtension

setup(
    name='extension',
    packages=['extension'],
    ext_modules=[CppExtension(
        name='extension',
        sources='extension.cpp',
    )],
    cmdclass=dict(build_ext=BuildExtension))
```

SETUPTOOLS

```python
import torch.utils.cpp_extension

module = torch.cpp_extension.load(
    name='extension',
    sources='extension.cpp',
)

module.compute(...)
```

JIT EXTENSION

```python
import torch
import extension

image = torch.randn(128, 128)
warp = torch.randn(3, 3)
output = extension.compute(image, warp)
```

PYTHON INTEGRATION

C++ FRONTEND

The aesthetics of imperative PyTorch for high performance, pure C++ research environments

MISSION

The aesthetics of PyTorch in pure C++

MOTIVATION

Enable research in environments that are . . .

MISSION

The aesthetics of PyTorch in pure C++

VALUES

Enable research in environments that are . . .

LOW LATENCY

BARE METAL

MULTITHREADED

ALREADY C++

torch::nn

NEURAL NETWORKS

torch::optim

OPTIMIZERS

torch::data

DATASETS & DATA LOADERS

torch::serialize

SERIALIZATION

torch::python

PYTHON INTER-OP

torch::jit

TORCH SCRIPT INTER-OP

```cpp
#include <torch/torch.h>

struct Net : torch::nn::Module {
  Net() : fc1(8, 64), fc2(64, 1) {
    register_module("fc1", fc1);
    register_module("fc2", fc2);
  }

  torch::Tensor forward(torch::Tensor x) {
    x = torch::relu(fc1->forward(x));
    x = torch::dropout(x, /*p=*/0.5);
    x = torch::sigmoid(fc2->forward(x));
    return x;
  }

  torch::nn::Linear fc1, fc2;
};
```

C++

```python
import torch

class Net(torch.nn.Module):
    def __init__(self):
        self.fc1 = torch.nn.Linear(8, 64)
        self.fc2 = torch.nn.Linear(64, 1)

    def forward(self, x):
        x = torch.relu(self.fc1.forward(x))
        x = torch.dropout(x, p=0.5)
        x = torch.sigmoid(self.fc2.forward(x))
        return x
```

PYTHON

```cpp
Net net;

auto data_loader = torch::data::data_loader(
  torch::data::datasets::MNIST("./data"));

torch::optim::SGD optimizer(net->parameters());

for (size_t epoch = 1; epoch <= 10; ++epoch) {
  for (auto batch : data_loader) {
    optimizer.zero_grad();
    auto prediction = net->forward(batch.data);
    auto loss = torch::nll_loss(prediction,
                                batch.label);
    loss.backward();
    optimizer.step();
  }
  if (epoch % 2 == 0)
    torch::save(net, "net.pt");
}
```

C++

```python
net = Net()

data_loader = torch.utils.data.DataLoader(
    torchvision.datasets.MNIST('./data'))

optimizer = torch.optim.SGD(net.parameters())

for epoch in range(1, 11):
    for data, target in data_loader:
        optimizer.zero_grad()
        prediction = net.forward(data)
        loss = F.nll_loss(prediction, target)
        loss.backward()
        optimizer.step()
    if epoch % 2 == 0:
        torch.save(net, "net.pt")
```

PYTHON

pytorch.org

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