PyTorch 1.0

Bringing Research and Production Together

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ENGINEERING LEAD I FACEBOOK AI

Agenda

1

AI @ Facebook

2

PyTorch Tech Deep Dive

3

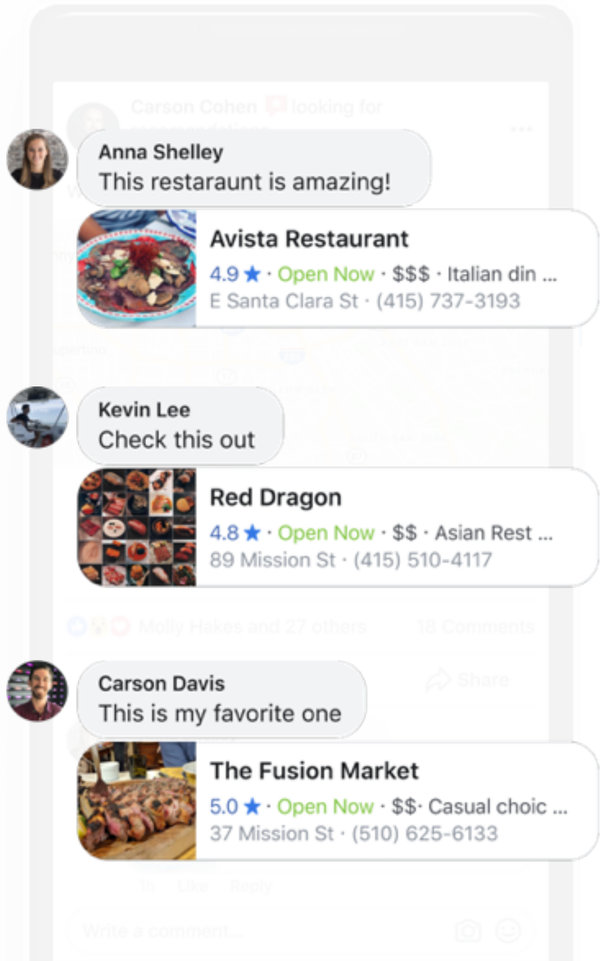
Bridging Research and Production

4

PyTorch Ecosystem

AI @ Facebook

SOCIAL RECOMMENDATIONS



ENHANCING EXISTING PRODUCTS

SOCIAL RECOMMENDATIONS

MACHINE TRANSLATIONS

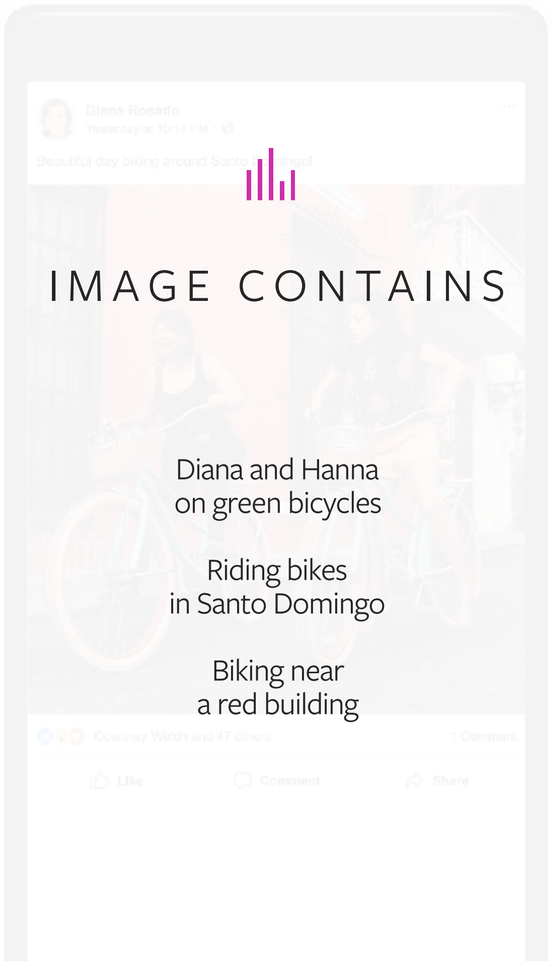
- 45+: Languages supported for translation
- 2K+: Translation directions
- 6B+: Translation impressions per day

ENHANCING EXISTING PRODUCTS

SOCIAL RECOMMENDATIONS

MACHINE TRANSLATIONS

ACCESSIBILITY



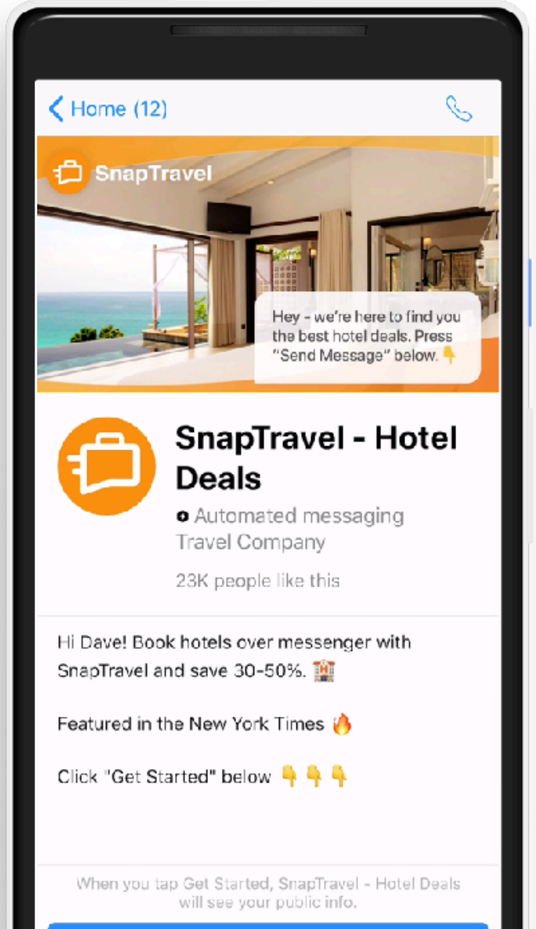
POWERING NEW EXPERIENCES

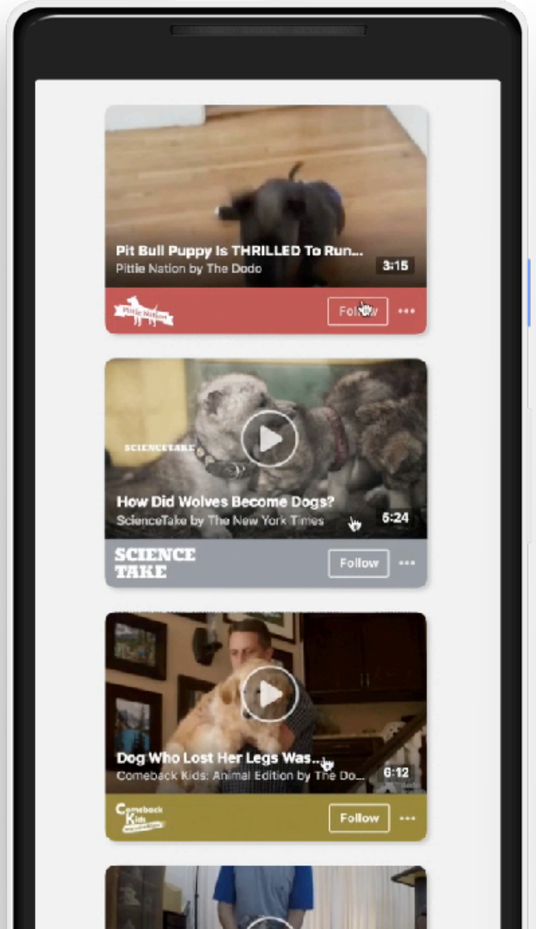
BOTS &
ASSISTANTS

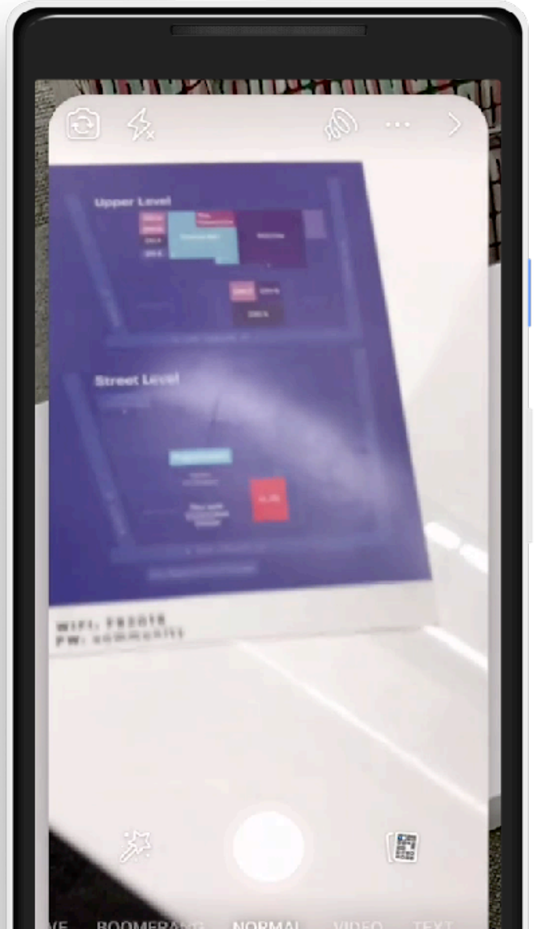
GENERATED
CONTENT

AR
EFFECTS

VR
HARDWARE

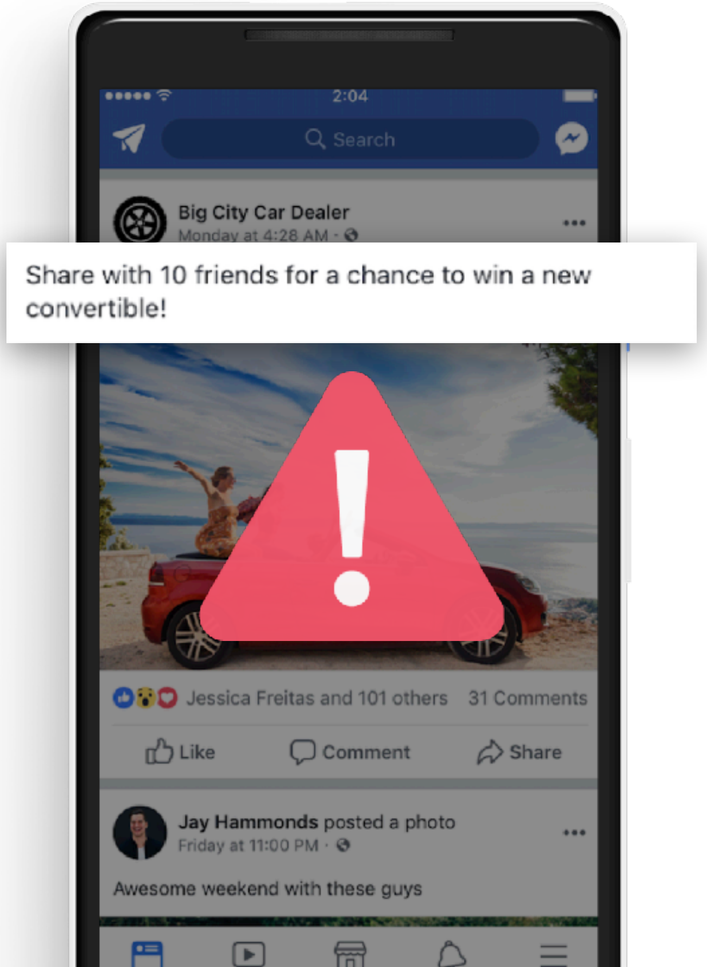






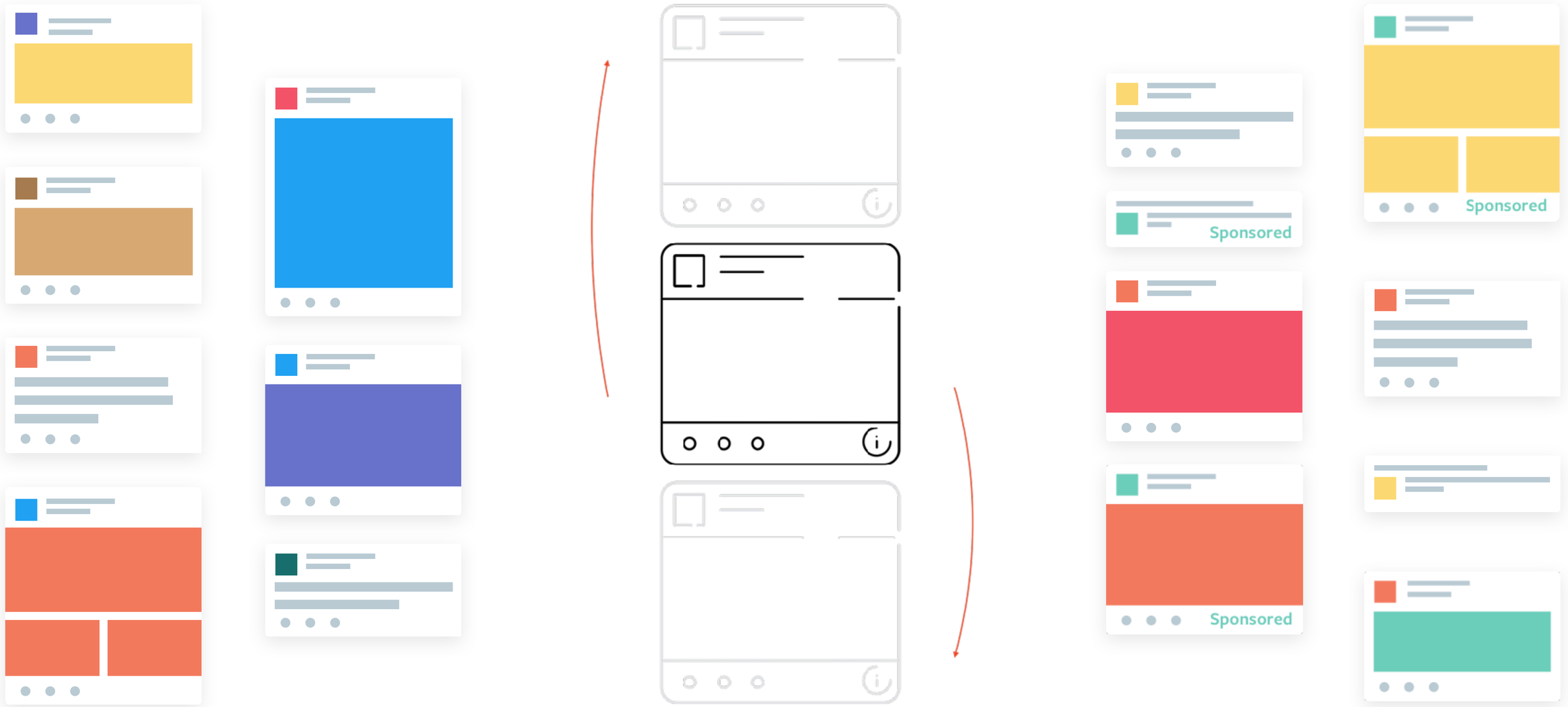
HELPING PROTECT COMMUNITY

SHARE BAITING



SUICIDE PREVENTION

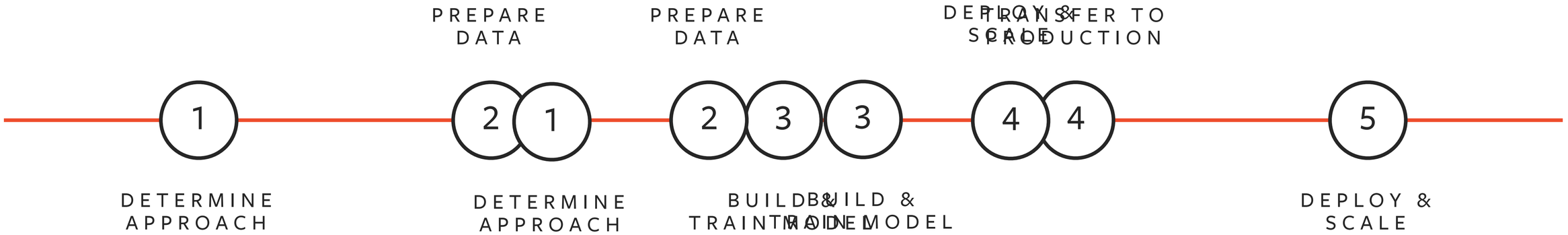
NEWS FEED & ADS CUSTOMIZATION



Machine Learning in Facebook Products

SUPPORT VECTOR MACHINES	GRADIENT-BOOSTED DECISION TREES	MULTI-LAYER PERCEPTRON	CONVOLUTIONAL NEURAL NETS	RECURRENT NEURAL NETS
SVM	GBDT	MLP	CNN	RNN
Facer	Integrity	News Feed	Facer	Language Translation
		ADS	Lumos	Speech Recognition
		SEARCH		Content Understanding
		Integrity		

Research to Production

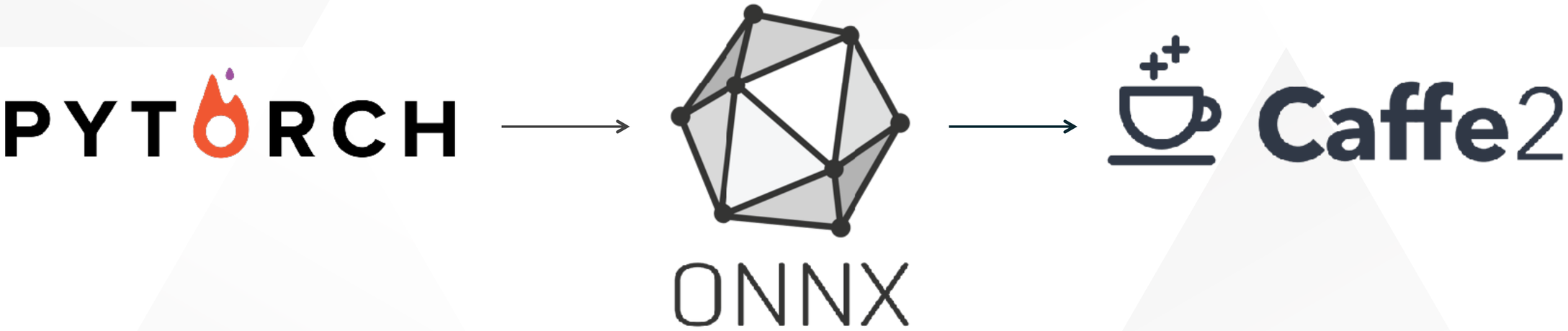

PREPARE DATA
PREPARE DATA
DEPLOY & SCALE
TRANSFER TO PRODUCTION
1
2
1
2
3
3
4
4
5
DETERMINE APPROACH
DETERMINE APPROACH
BUILD & TRAIN MODEL
BUILD & TRAIN MODEL
DEPLOY & SCALE

Research to Production at Facebook – Early 2017

REIMPLEMENTATION TAKES WEEKS OR MONTHS

Research to Production at Facebook – Early 2018

ENABLING MODEL OR MODEL FRAGMENT TRANSFER



Research to Production at Facebook

PYTORCH

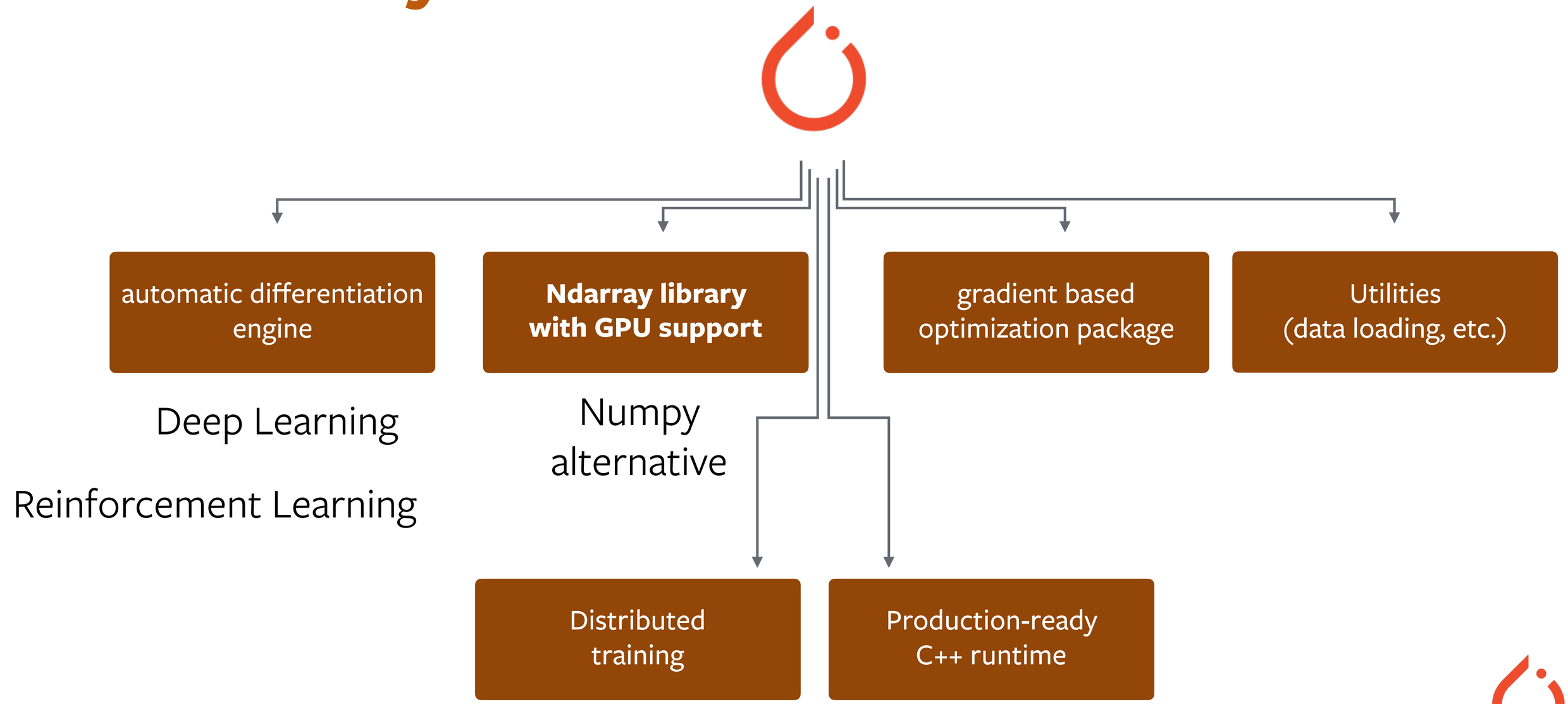
Caffe2

CORE TENETS

1. User-Centric
2. Community-Driven
3. Interoperable & Modular

What is PyTorch?

What is PyTorch?



ndarray library

- np.ndarray <-> torch.Tensor
- 200+ operations, similar to numpy
- very fast acceleration on NVIDIA GPUs

Numpy

```
# -*- coding: utf-8 -*-
import numpy as np

# N is batch size; D_in is input dimension;
# H is hidden dimension; D_out is output dimension.
N, D_in, H, D_out = 64, 1000, 100, 10

# Create random input and output data
x = np.random.randn(N, D_in)
y = np.random.randn(N, D_out)

# Randomly initialize weights
w1 = np.random.randn(D_in, H)
w2 = np.random.randn(H, D_out)

learning_rate = 1e-6
for t in range(500):
    # Forward pass: compute predicted y
    h = x.dot(w1)
    h_relu = np.maximum(h, 0)
    y_pred = h_relu.dot(w2)

    # Compute and print loss
    loss = np.square(y_pred - y).sum()
    print(t, loss)

    # Backprop to compute gradients of w1 and w2 with respect to loss
    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.T.dot(grad_y_pred)
    grad_h_relu = grad_y_pred.dot(w2.T)
    grad_h = grad_h_relu.copy()
    grad_h[h < 0] = 0
    grad_w1 = x.T.dot(grad_h)

    # Update weights
    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch

```
import torch


dtype = torch.FloatTensor
# dtype = torch.cuda.FloatTensor # Uncomment this to run on GPU

# N is batch size; D_in is input dimension;
# H is hidden dimension; D_out is output dimension.
N, D_in, H, D_out = 64, 1000, 100, 10

# Create random input and output data
x = torch.randn(N, D_in).type(dtype)
y = torch.randn(N, D_out).type(dtype)

# Randomly initialize weights
w1 = torch.randn(D_in, H).type(dtype)
w2 = torch.randn(H, D_out).type(dtype)

learning_rate = 1e-6
for t in range(500):
    # Forward pass: compute predicted y
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)

    # Compute and print loss
    loss = (y_pred - y).pow(2).sum()
    print(t, loss)

    # Backprop to compute gradients of w1 and w2 with respect to loss
    grad_y_pred = 2.0 * (y_pred - y)
    grad_w2 = h_relu.t().mm(grad_y_pred)
    grad_h_relu = grad_y_pred.mm(w2.t())
    grad_h = grad_h_relu.clone()
    grad_h[h < 0] = 0
    grad_w1 = x.t().mm(grad_h)

    # Update weights using gradient descent
    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

ndarray / Tensor library

Tensors are similar to numpy's ndarrays, with the addition being that Tensors can also be used on a GPU to accelerate computing.

```
from __future__ import print_function
import torch
```

Construct a 5x3 matrix, uninitialized:

```
x = torch.Tensor(5, 3)
print(x)
```

Out:

```
1.00000e-25 *
  0.4136  0.0000  0.0000
  0.0000  1.6519  0.0000
  1.6518  0.0000  1.6519
  0.0000  1.6518  0.0000
  1.6520  0.0000  1.6519
[torch.FloatTensor of size 5x3]
```

ndarray / Tensor library

Construct a randomly initialized matrix

```
x = torch.rand(5, 3)
print(x)
```

Out:

```
0.2598  0.7231  0.8534
 0.3928  0.1244  0.5110
 0.5476  0.2700  0.5856
 0.7288  0.9455  0.8749
 0.6663  0.8230  0.2713
[torch.FloatTensor of size 5x3]
```

Get its size

```
print(x.size())
```

Out:

```
torch.Size([5, 3])
```

ndarray / Tensor library

You can use standard numpy-like indexing with all bells and whistles!

```
print(x[:, 1])
```

Out:

```
0.7231
 0.1244
 0.2700
 0.9455
 0.8230
[torch.FloatTensor of size 5]
```

NumPy bridge

Converting torch Tensor to numpy Array

```
a = torch.ones(5)
print(a)
```

Out:

```
1
 1
 1
 1
 1
[torch.FloatTensor of size 5]
```

```
b = a.numpy()
print(b)
```

Out:

```
[ 1.  1.  1.  1.  1.]
```

NumPy bridge

Converting torch Tensor to numpy Array

```
a = torch.ones(5)
print(a)
```

Out:

```
1
 1
 1
 1
 1
[torch.FloatTensor of size 5]
```

Zero memory-copy
very efficient

```
b = a.numpy()
print(b)
```

Out:

```
[ 1.  1.  1.  1.  1.]
```

NumPy bridge

See how the numpy array changed in value.

```
a.add_(1)
print(a)
print(b)
```

Out:

```
2
 2
 2
 2
 2
[torch.FloatTensor of size 5]

[ 2.  2.  2.  2.  2.]
```

NumPy bridge

Converting numpy Array to torch Tensor

See how changing the np array changed the torch Tensor automatically

```
import numpy as np
a = np.ones(5)
b = torch.from_numpy(a)
np.add(a, 1, out=a)
print(a)
print(b)
```

Out:

```
[ 2.  2.  2.  2.  2.]

 2
 2
 2
 2
 2
[torch.DoubleTensor of size 5]
```

All the Tensors on the CPU except a CharTensor support converting to NumPy and back.

Seamless GPU Tensors

CUDA Tensors

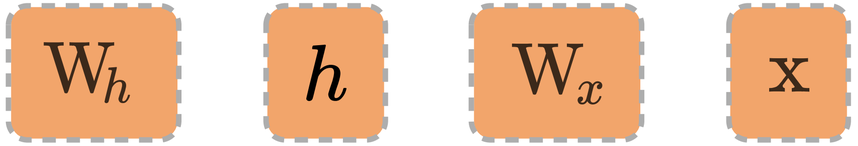
Tensors can be moved onto GPU using the `.cuda` function.

```
# let us run this cell only if CUDA is available
if torch.cuda.is_available():
    x = x.cuda()
    y = y.cuda()
    x + y
```

automatic differentiation engine

for deep learning and reinforcement learning

PyTorch Autograd

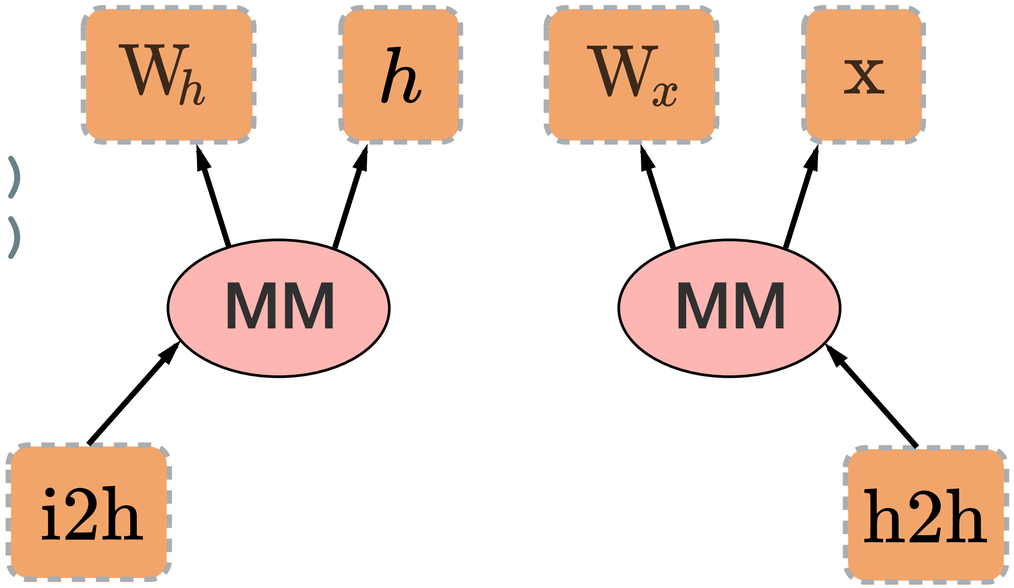



```
W_h = torch.randn(20, 20, requires_grad=True)
W_x = torch.randn(20, 10, requires_grad=True)
x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)
```

PyTorch Autograd

```
W_h = torch.randn(20, 20, requires_grad=True)
W_x = torch.randn(20, 10, requires_grad=True)
x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)


i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
```



PyTorch Autograd

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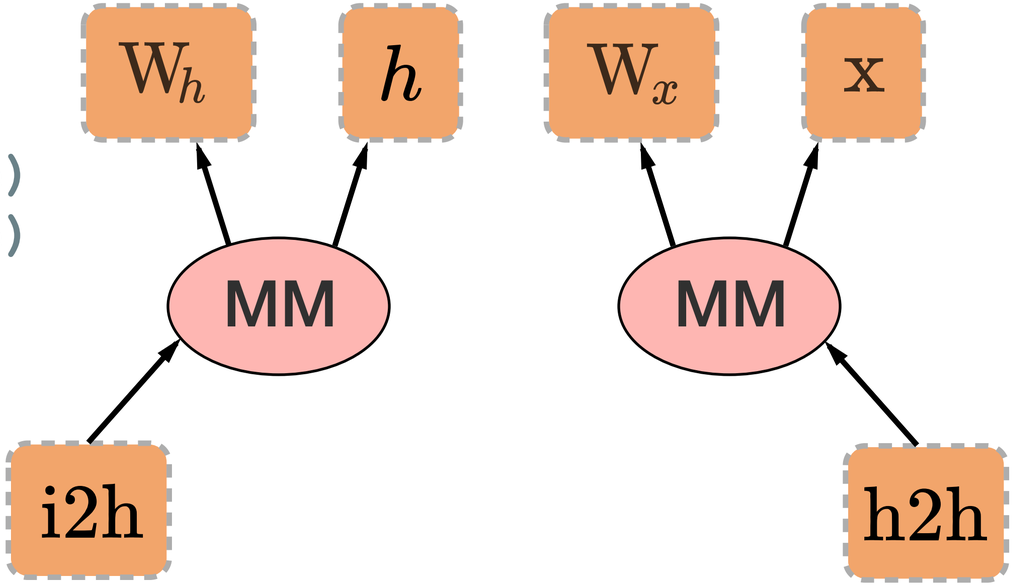
x = torch.randn(1, 10)
prev_h = torch.randn(1, 20)


i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
next_h = i2h + h2h
```



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```

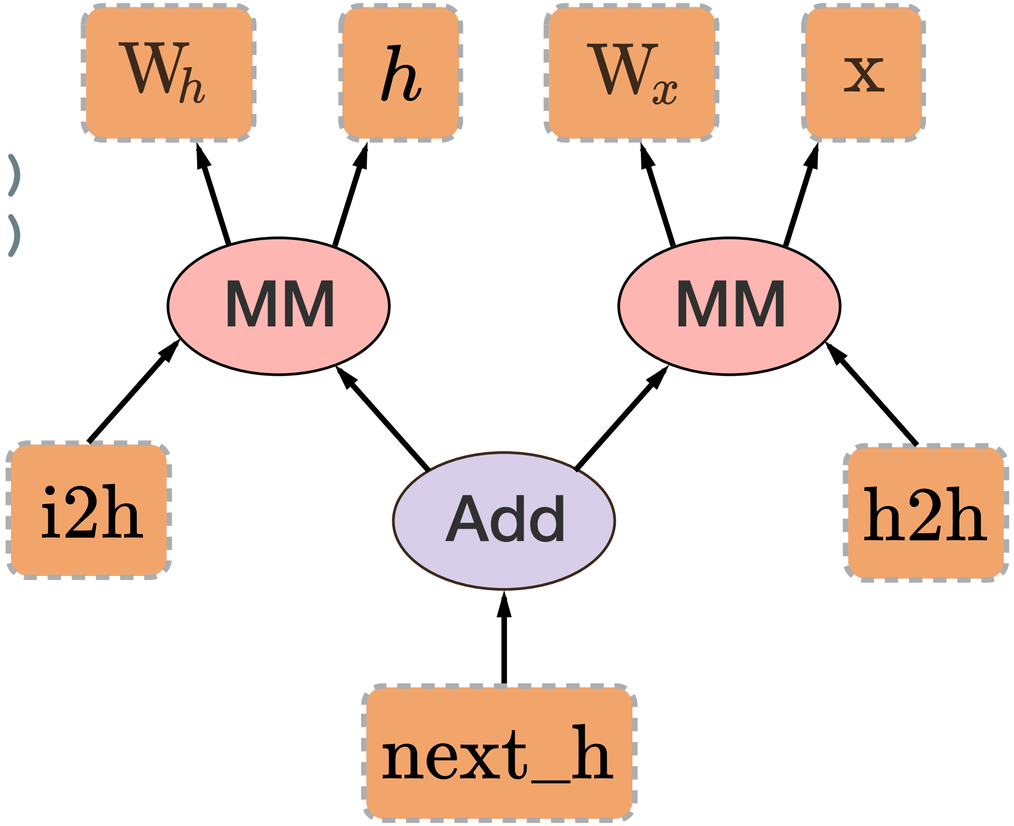

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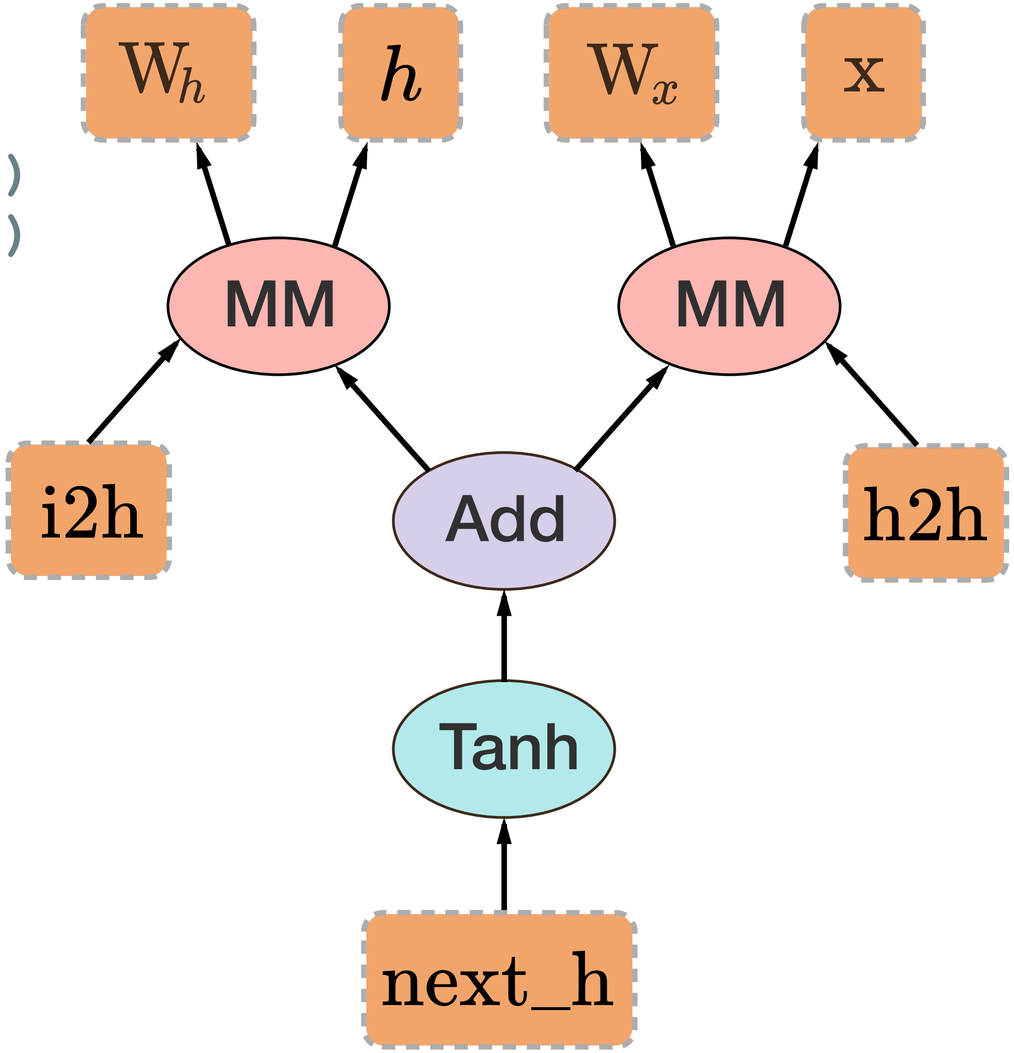
i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
next_h = i2h + h2h
next_h = next_h.tanh()
```



PyTorch Autograd

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i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
next_h = i2h + h2h
next_h = next_h.tanh()

next_h.backward(torch.ones(1, 20))
```

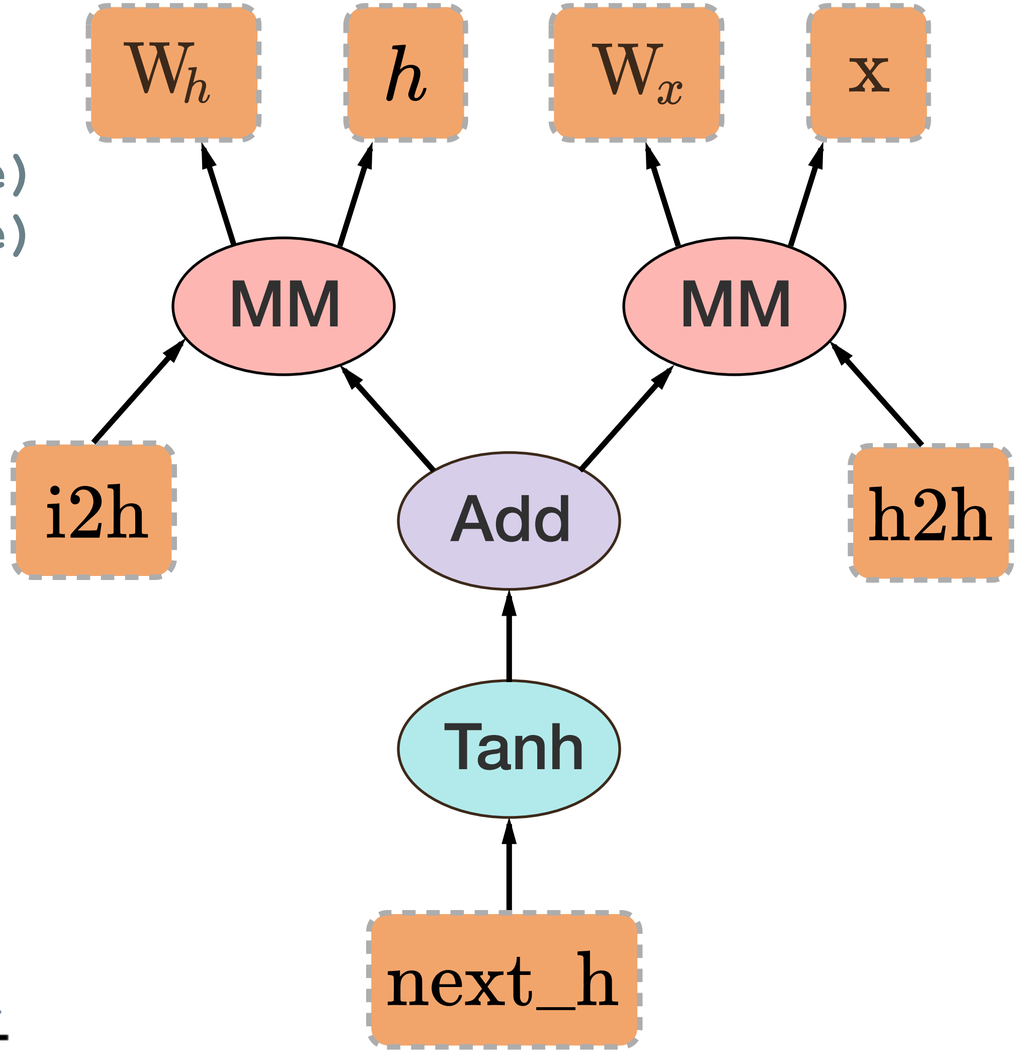

$$\frac{dnext_h}{dW_h}$$

$$W_h = W_h - \alpha * \frac{dnext_h}{dW_h}$$

Neural Networks

```
1   class Net(nn.Module):
2       def __init__(self):
3           super(Net, self).__init__()
4           self.conv1 = nn.Conv2d(1, 10, kernel_size=5)
5           self.conv2 = nn.Conv2d(10, 20, kernel_size=5)
6           self.conv2_drop = nn.Dropout2d()
7           self.fc1 = nn.Linear(320, 50)
8           self.fc2 = nn.Linear(50, 10)
9
10      def forward(self, x):
11          x = F.relu(F.max_pool2d(self.conv1(x), 2))
12          x = F.relu(F.max_pool2d(self.conv2_drop(self.conv2(x)), 2))
13          x = x.view(-1, 320)
14          x = F.relu(self.fc1(x))
15          x = F.dropout(x, training=self.training)
16          x = self.fc2(x)
17          return F.log_softmax(x)
18
19  model = Net()
20  input = Variable(torch.randn(10, 20))
21  output = model(input)
```

Neural Networks

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17          return F.log_softmax(x)
18
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21  output = model(input)
```

Optimization package

SGD, Adagrad, RMSProp, LBFGS, etc.

```
net = Net()
optimizer = torch.optim.SGD(net.parameters(), lr=0.01, momentum=0.9)

for input, target in dataset:
    optimizer.zero_grad()
    output = model(input)
    loss = F.cross_entropy(output, target)
    loss.backward()
    optimizer.step()
```

Debugging

- PyTorch is a Python extension

Debugging

- PyTorch is a Python extension
- Use your favorite Python debugger

Debugging

- PyTorch is a Python extension
- Use your favorite Python debugger
- Use the most popular debugger:

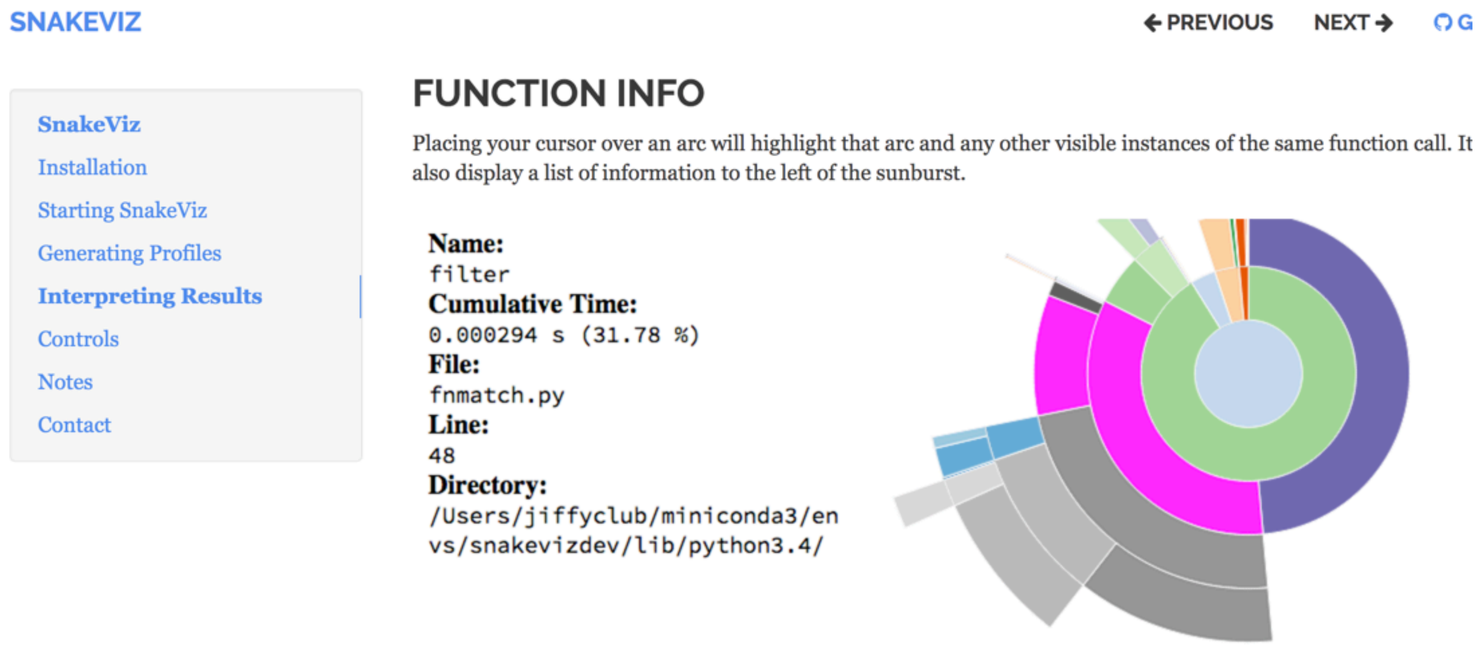
Debugging

- PyTorch is a Python extension
- Use your favorite Python debugger
- Use the most popular debugger:

```
print(foo)
```

Identifying bottlenecks

- PyTorch is a Python extension
- Use your favorite Python profiler



Identifying bottlenecks

- PyTorch is a Python extension
- Use your favorite Python profiler: Line_Profiler

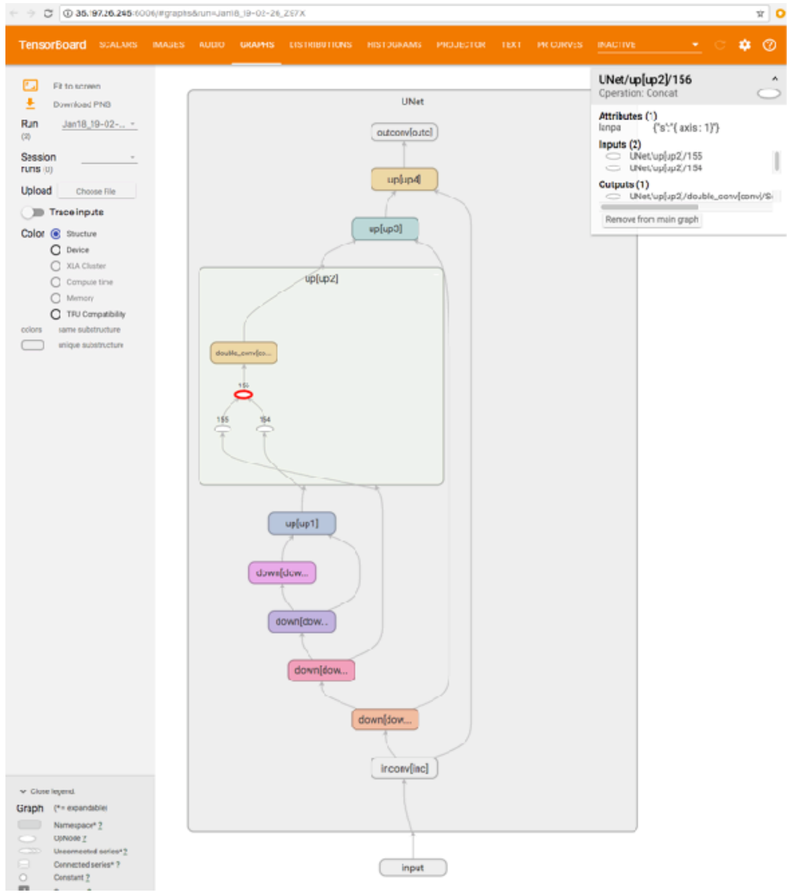
```
File: pystone.py
Function: Proc2 at line 149
Total time: 0.606656 s

Line #      Hits         Time  Per Hit   % Time  Line Contents
==============================================================
   149                                           @profile
   150                                           def Proc2(IntParIO):
   151     50000        82003      1.6     13.5      IntLoc = IntParIO + 10
   152     50000        63162      1.3     10.4      while 1:
   153     50000        69065      1.4     11.4          if Char1Glob == 'A':
   154     50000        66354      1.3     10.9              IntLoc = IntLoc - 1
   155     50000        67263      1.3     11.1              IntParIO = IntLoc - IntGlob
   156     50000        65494      1.3     10.8              EnumLoc = Ident1
   157     50000        68001      1.4     11.2          if EnumLoc == Ident1:
   158     50000        63739      1.3     10.5              break
   159     50000        61575      1.2     10.1      return IntParIO
```

Visualization

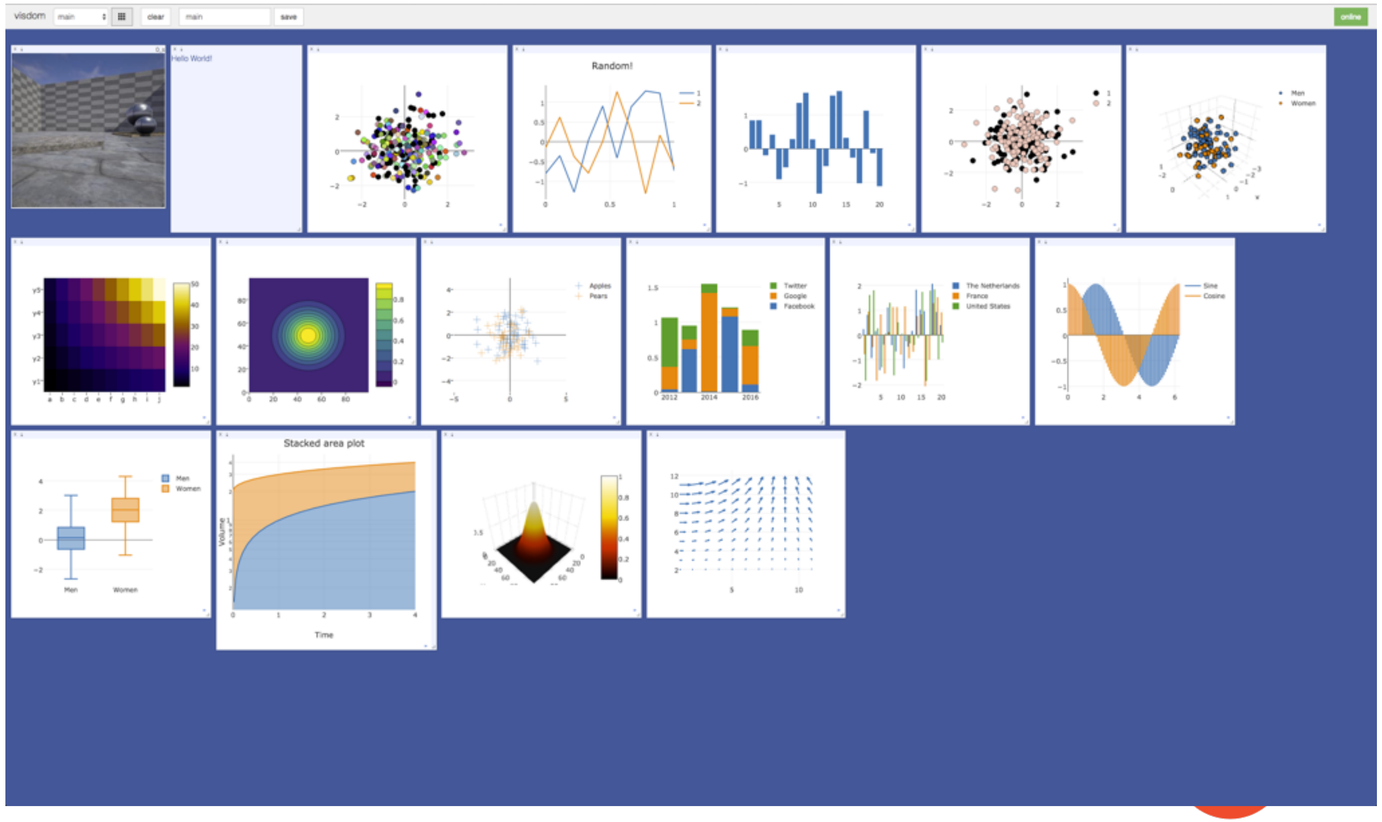
TensorBoard-PyTorch

https://github.com/lanpa/tensorboard-pytorch



Visdom

https://github.com/facebookresearch/visdom



Work items in practice

Writing Dataset loaders

Building models

Implementing Training loop

Checkpointing models

Python + PyTorch - an environment to do all of this

Interfacing with environments

Building optimizers

Dealing with GPUs

Building Baselines

Work items in practice

Writing Dataset loaders

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Python + PyTorch - an environment to do all of this

Interfacing with environments

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Building Baselines

+ tools for making your model production-ready

Distributed training

Performance optimization

Deployment for inference

Imperative vs Declarative Toolkits

DEVELOPER EFFICIENCY

- Debuggability
- Interactivity
- Simplicity
- Intuitiveness

INFRASTRUCTURE EFFICIENCY

- Efficiency
- Reliability
- Scalability
- Cross Platform

COMPUTATION GRAPH

Declarative Toolkits

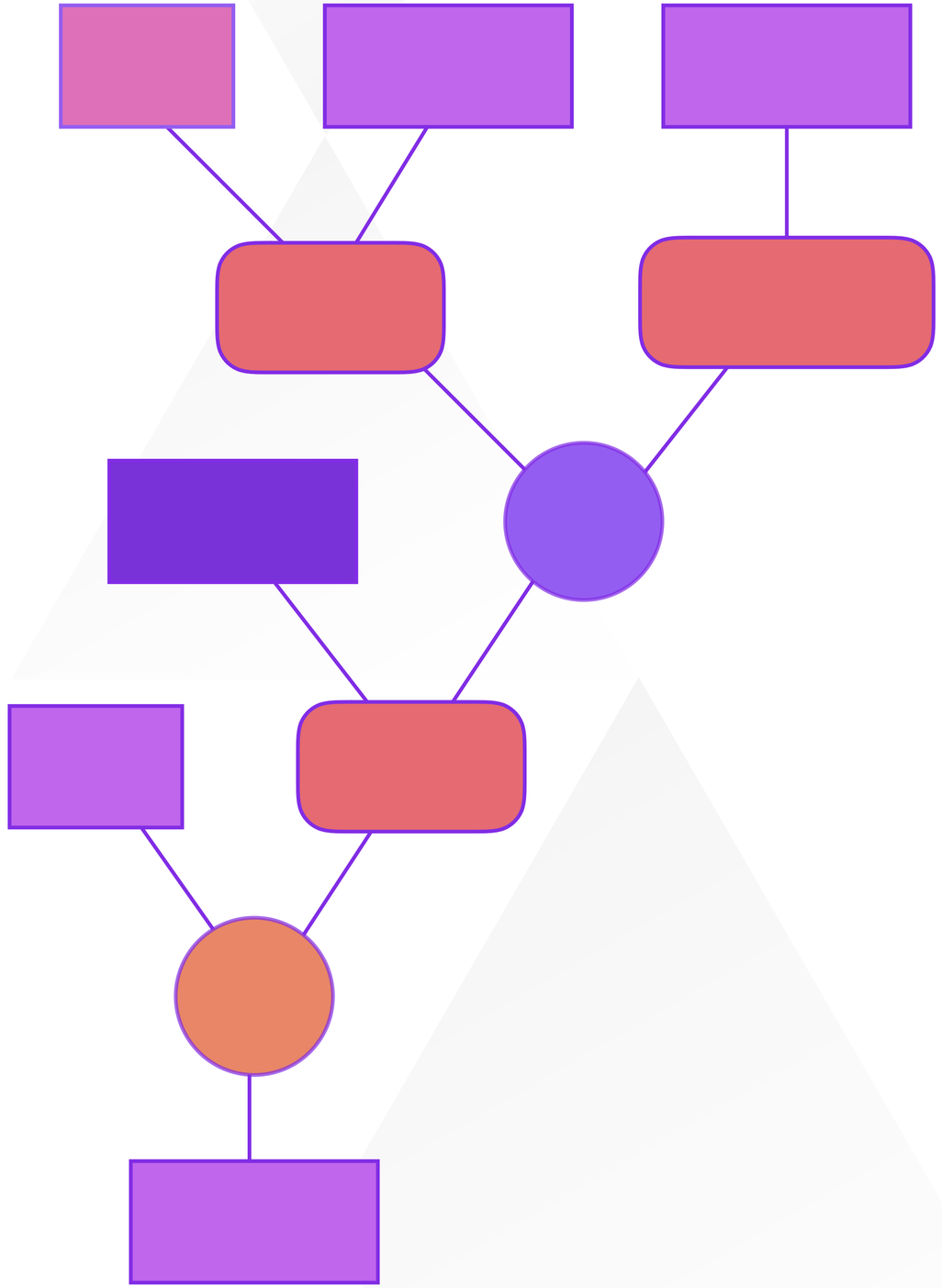
theano

Caffe

mxnet

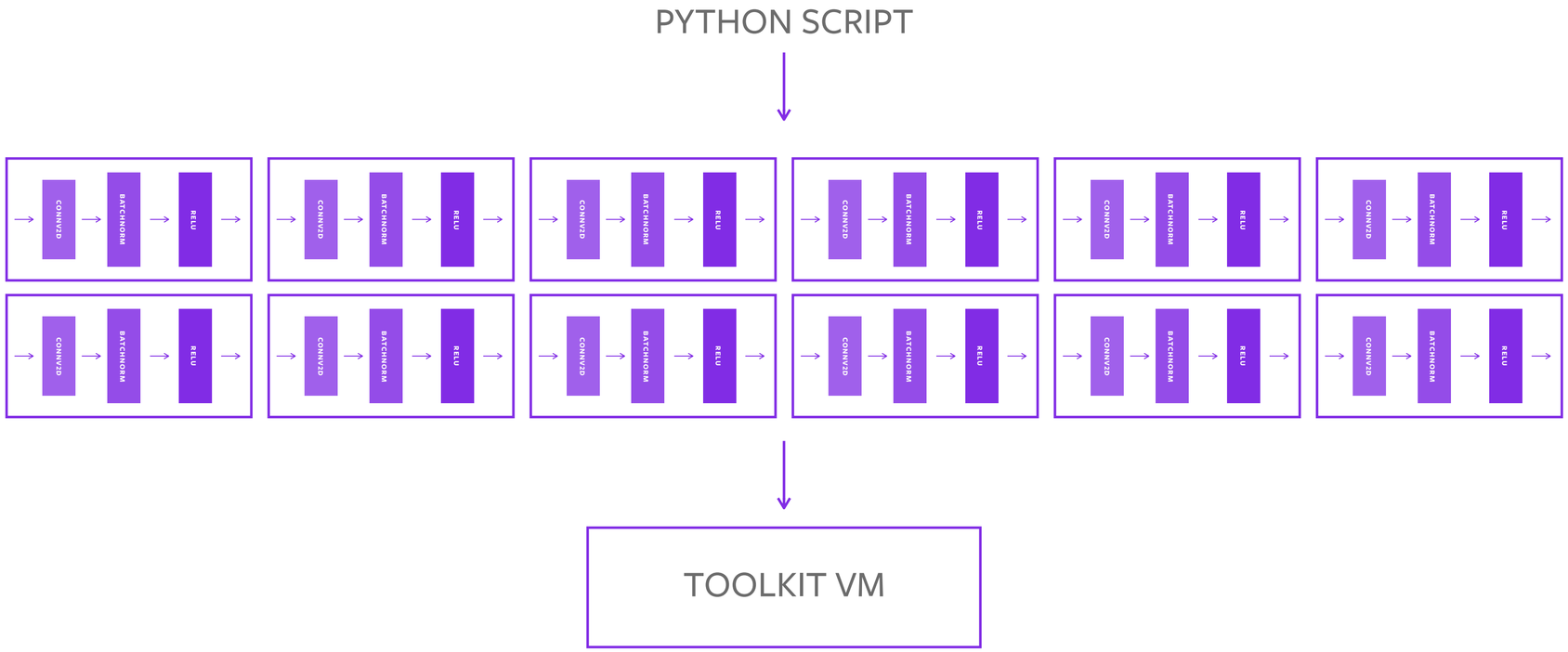
Caffe2

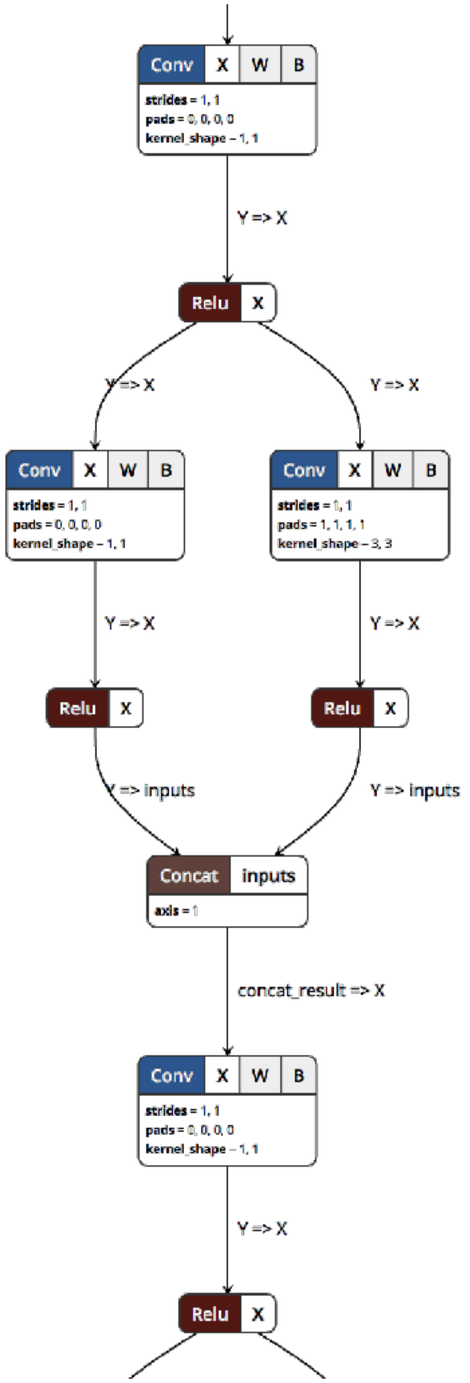
TensorFlow



DECLARATIVE TOOLKITS

Declare and compile a model
Repeatedly execute the model in a VM





DOCUMENTATION

Relu

Relu takes one input data (Tensor) and produces one output data (Tensor) where the rectified linear function, y = max(0, x), is applied to the tensor elementwise.

Attributes

consumed_inputs: `int[]`
legacy optimization attribute.

Inputs

X: `T`
Input tensor

Outputs

Y: `T`
Output tensor

Type Constraints

T: `tensor(float16)`, `tensor(float)`, `tensor(double)`
Constrain input and output types to float tensors.

Examples

relu

```
node = onnx.helper.make_node(
    'Relu',
    inputs=['x'],
    outputs=['y'],
)
x = np.random.randn(3, 4, 5).astype(np.float32)
y = np.clip(x, 0, np.inf)

expect(node, inputs=[x], outputs=[y],
       name='test_relu')
```

Support

In domain `ai.onnx` since version `1` at support level `common`.

Computation Graph

DECLARATIVE TOOLKITS

- Declare a computation
- Placeholder variables
- Compile it
- Run it in a Session

```
import tensorflow as tf
import numpy as np
trX = np.linspace(-1, 1, 101)
trY = 2 * trX + np.random.randn(*trX.shape) * 0.33
X = tf.placeholder("float")
Y = tf.placeholder("float")
def model(X, w):
        return tf.multiply(X, w)
w = tf.Variable(0.0, name="weights")
y_model = model(X, w)
cost = tf.square(Y - y_model)
train_op = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
with tf.Session() as sess:
        tf.global_variables_initializer().run()
        for i in range(100):
            for (x, y) in zip(trX, trY):
                sess.run(train_op, feed_dict={X: x, Y: y})
        print(sess.run(w))
```

Computation Graph

DECLARATIVE TOOLKITS

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import numpy as np
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Computation Graph

DECLARATIVE TOOLKITS

- Declare a computation
- Placeholder variables
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import numpy as np
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trY = 2 * trX + np.random.randn(*trX.shape) * 0.33
X = tf.placeholder("float")
```

Model definition

```
def model(X, w):
        return tf.multiply(X, w)
w = tf.Variable(0.0, name="weights")
y_model = model(X, w)
cost = tf.square(Y - y_model)
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Computation Graph

DECLARATIVE TOOLKITS

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        return tf.multiply(X, w)
w = tf.Variable(0.0, name="weights")
y_model = model(X, w)
cost = tf.square(Y - y_model)
train_op = tf.train.GradientDescentOptimizer(0.01).minimize(cost)
```

```
for i in range(100):
    for (x, y) in zip(trX, trY):
        sess.run(train_op, feed_dict={X: x, Y: y})
print(sess.run(w))
```

A separate, Turing complete, virtual machine.

Computation Graph

DECLARATIVE TOOLKITS

- Declare a computation
- Placeholder variables
- Compile it
- Run it in a Session

ADVANTAGES

End-to-end program optimization

Easy to serialize for production deployment

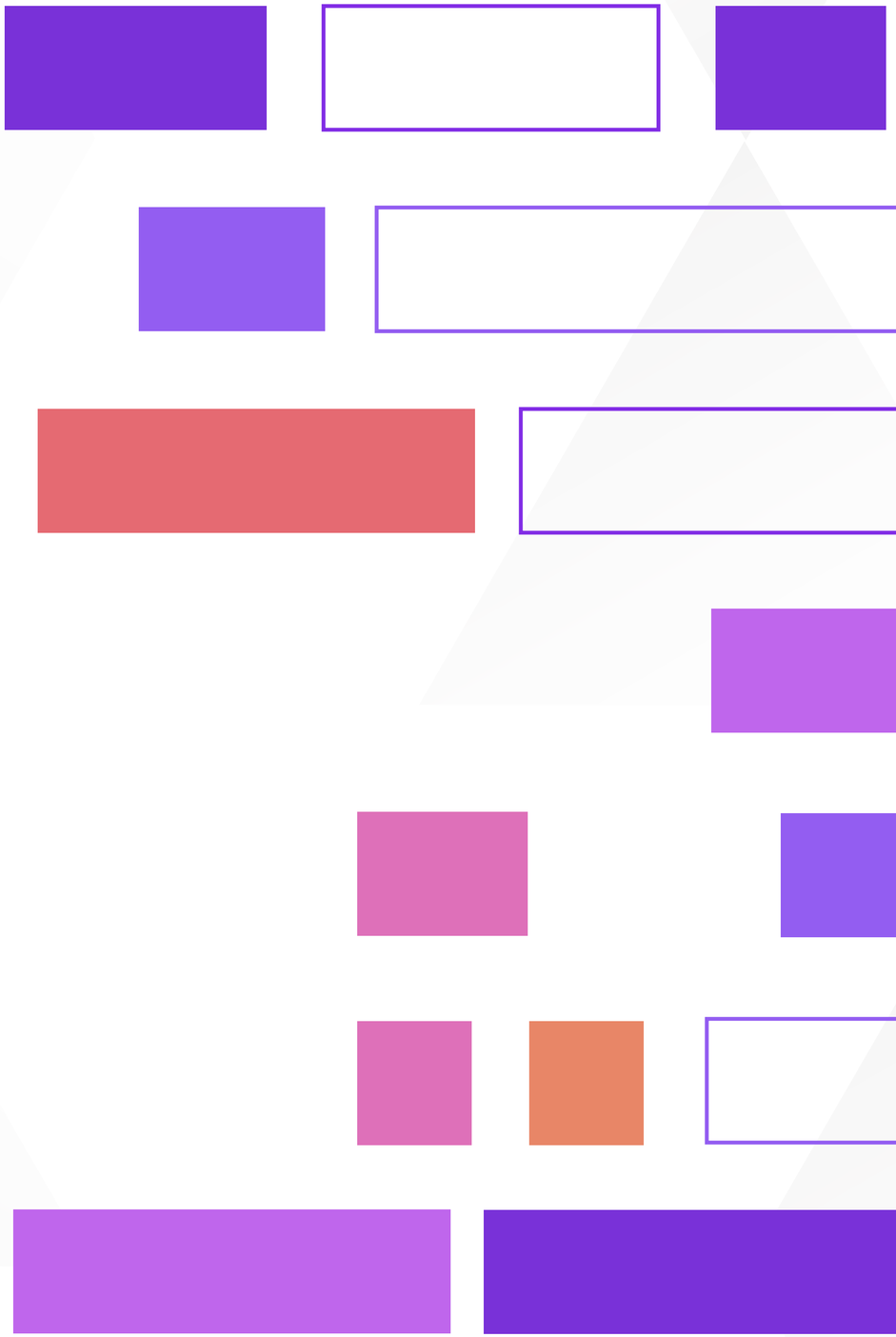
DISADVANTAGES

Non-intuitive programing model

Difficult to design and maintain

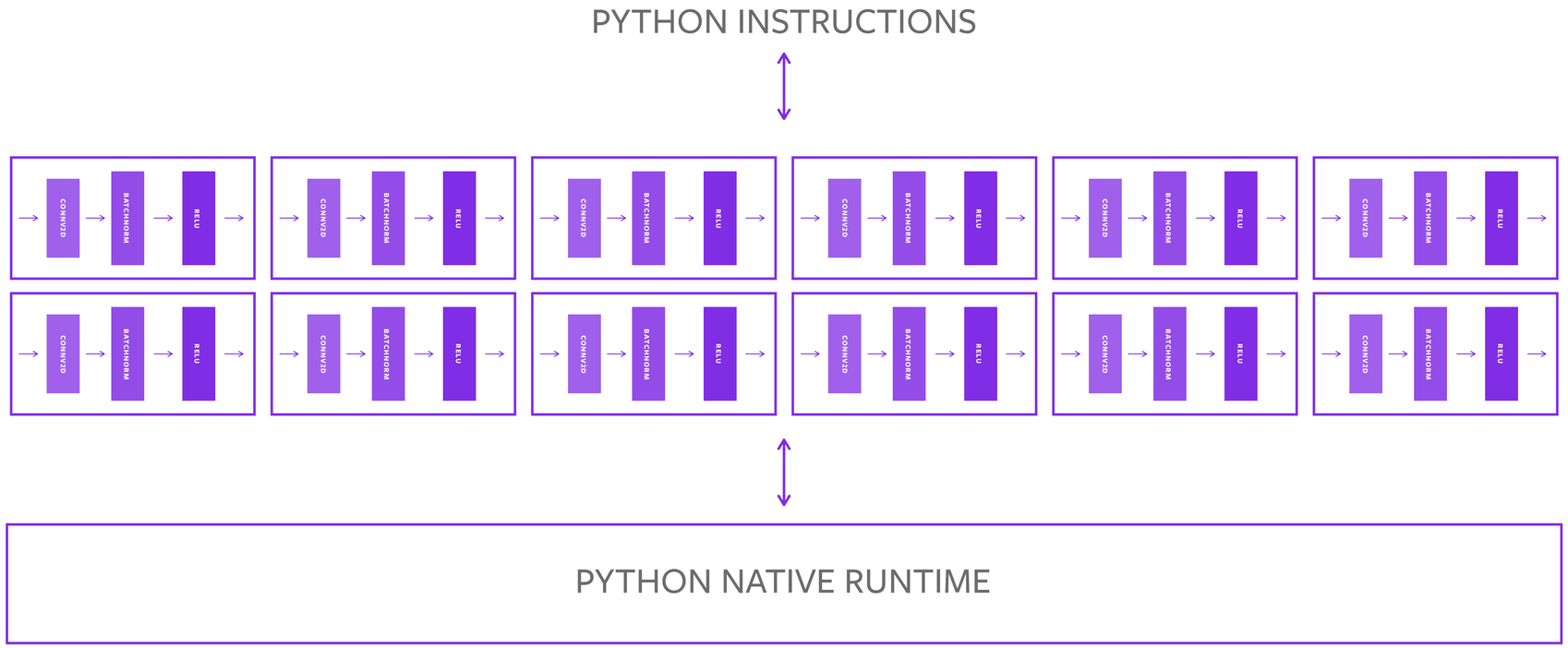
DEFINE-BY-RUN

Imperative Toolkits



IMPERATIVE TOOLKITS

Run a series of computation
Implicitly defining the model as execution goes



Imperative Toolkits

- Define a model by execution
- No separate compilation stage
- No separate execution engine

```
import torch
from torch.autograd import Variable

trX = torch.linspace(-1, 1, 101)
trY = 2 * trX + torch.random(*trX.size()) * 0.33

w = Variable(trX.new([0.0]), requires_grad=True)

for i in range(100):
    for (x, y) in zip(trX, trY):
        X = Variable(x)
        Y = Variable(y)
        print(X)
        print(Y)

        y_model = X * w.expand_as(X)
cost = (Y - y_model) * 2
Cost.backward(torch.ones(*cost.size()))

w.data = w.data + 0.01 * w.grad.data

print(w)
```

Imperative Toolkits

- Define a model by execution
- No separate compilation stage
- No separate execution engine

Model constructed and values computed as we define it.

```
trX = torch.linspace(-1, 1, 101)
trY = 2 * trX + torch.random(*trX.size()) * 0.33

w = Variable(trX.new([0.0]), requires_grad=True)

for i in range(100):
    for (x, y) in zip(trX, trY):
        X = Variable(x)
        Y = Variable(y)
        print(X)
        print(Y)

        y_model = X * w.expand_as(X)
cost = (Y - y_model) * 2
Cost.backward(torch.ones(*cost.size()))

w.data = w.data + 0.01 * w.grad.data

print(w)
```

Imperative Toolkits

- Define a model by execution
- No separate compilation stage
- No separate execution engine

ADVANTAGES

Natural, flexible program model

Ability to use Python ecosystem

Easy to debug

DISADVANTAGES

Difficult to optimize

No clear model serialization

Overhead can be significant

Bridging Imperative and Declarative

PyTorch *Eager Mode*

Models are Python program,
autograd for derivatives

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

– Needs Python to run
– Difficult to optimize and parallelize

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

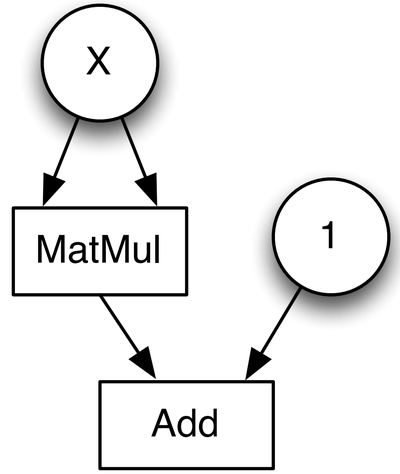
For use at scale in production

Tracing

```
def foo(x, t):
  y = x.mm(x)
  print(y) # still works!
  return y + t

x = torch.Tensor([[1,2],[3,4]])
foo(x, 1)

trace = torch.jit.trace(foo, (x, 1))
trace.save(“serialized.pt”)
```

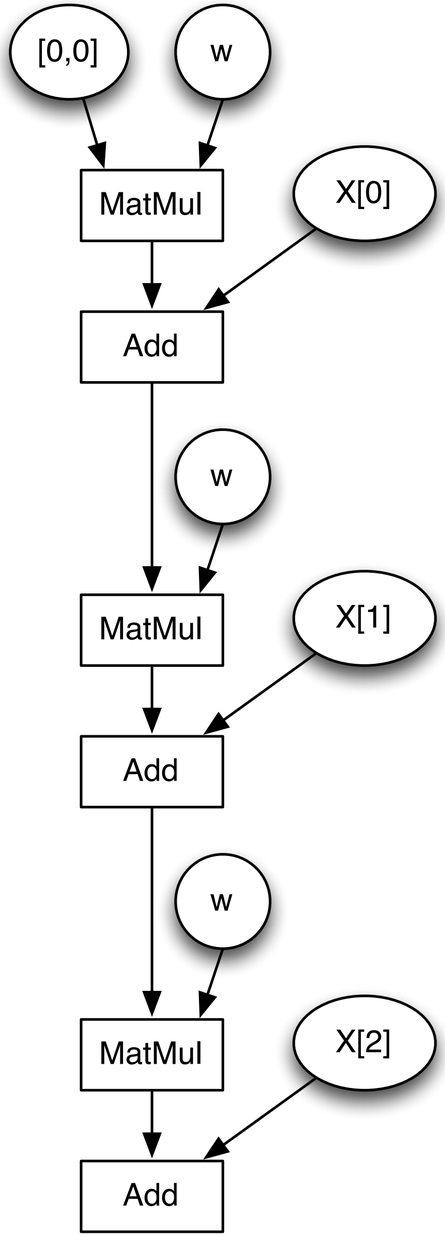


Tracing

```
def foo(x, t):
  y = x.mm(x)
  print(y) # still works!
  return y + t

def bar(x, w):
    y = torch.zeros(1, 2)
    for t in x:
        y = foo(y, w, t)
    return y

trace = torch.jit.trace(foo, (x, 1))
trace.save(“serialized.pt”)
```

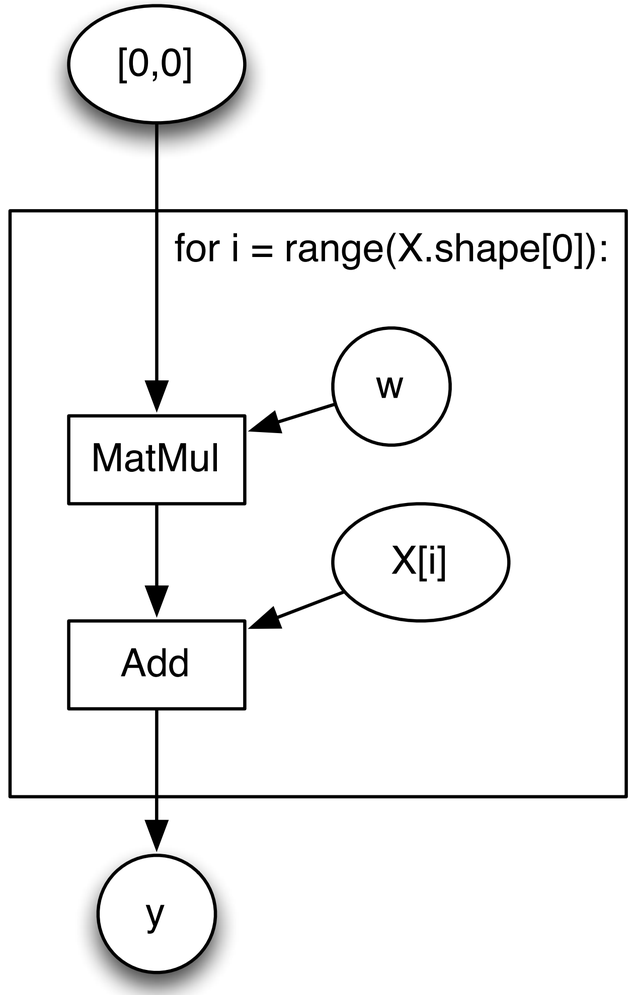


Script

```
def foo(x, t):
  y = x.mm(x)
  print(y) # still works!
  return y + t

@script
def bar(x, w):
    y = torch.zeros(1, 2)
    for t in x:
        y = foo(y, w, t)
    return y

trace = torch.jit.trace(foo, (x, 1))
trace.save("serialized.pt")
```



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';
```

PREVIEW RELEASE

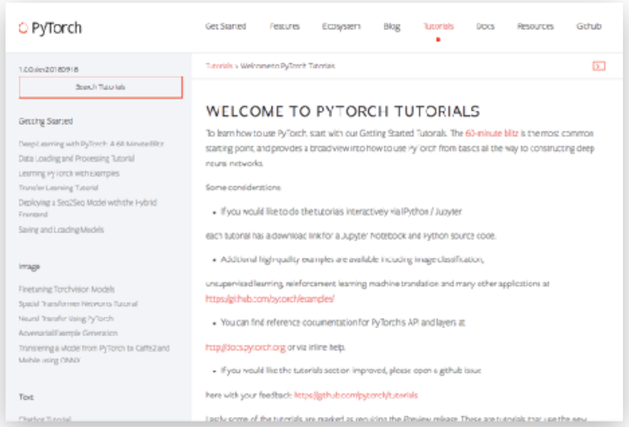
Try the PyTorch JIT today

INSTALL

Using the nightly preview builds of PyTorch.

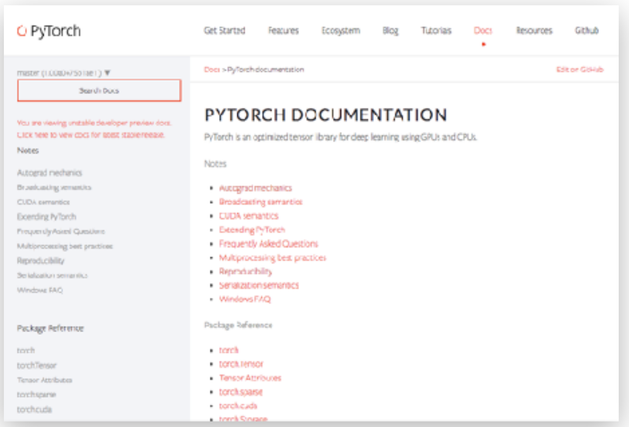
TUTORIALS

How to use tracing and script to export a sequence to sequence model.

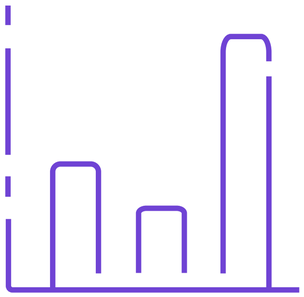


DOCS

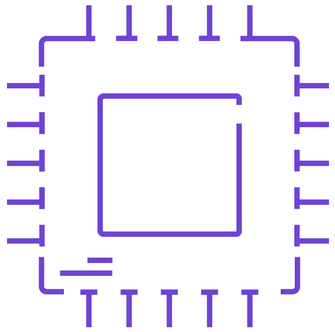
API and language reference for Torch Script.



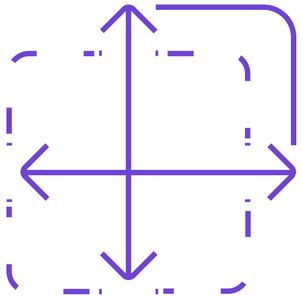
Scale



MORE DATA



FASTER COMPUTE



MODEL EXPLORATION

JUN 8, 2017 - Facebook

Accelerating machine learning for computer vision

https://code.fb.com/core-data/accelerating-machine-learning-for-computer-vision/

MAY 2, 2018 - Facebook

Advancing state-of-the-art image recognition with deep learning on hashtags

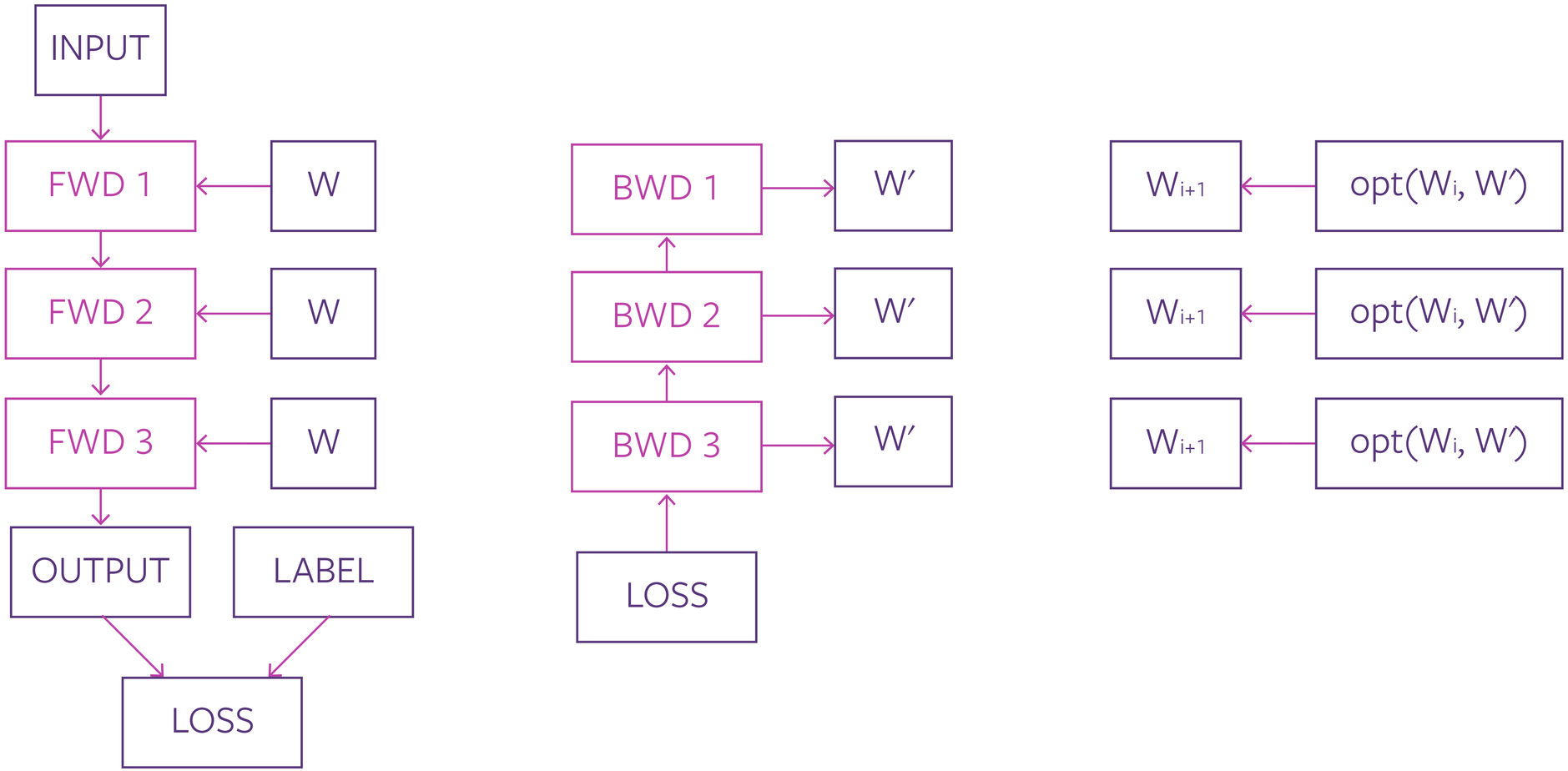
https://code.fb.com/ml-applications/advancing-state-of-the-art-image-recognition-with-deep-learning-on-hashtags/

AUG 10, 2018 - fast.ai

Now anyone can train ImageNet in 18 minutes

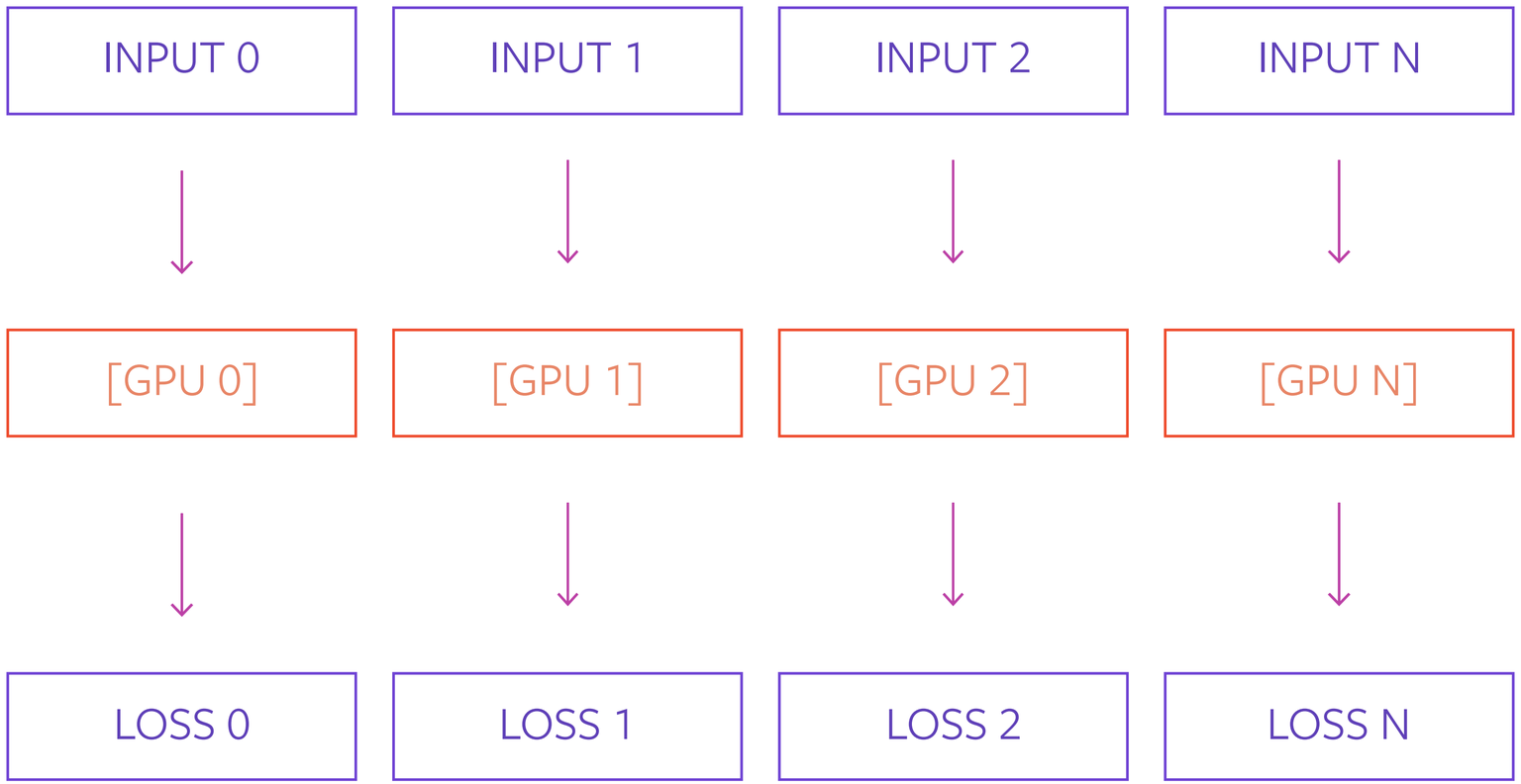
http://www.fast.ai/2018/08/10/fastai-diu-imagenet/

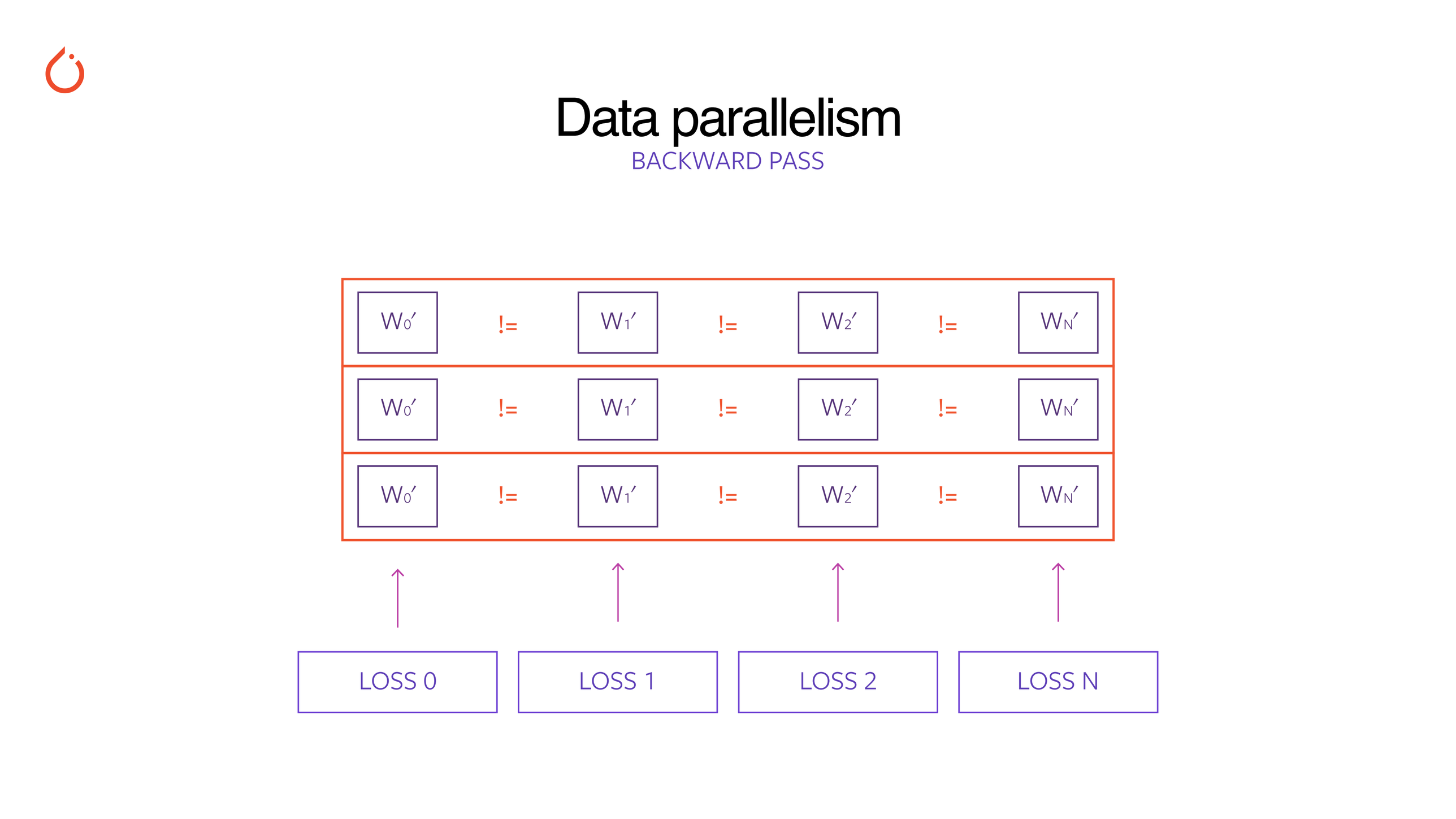
Anatomy of a single iteration



Data parallelism

FORWARD PASS

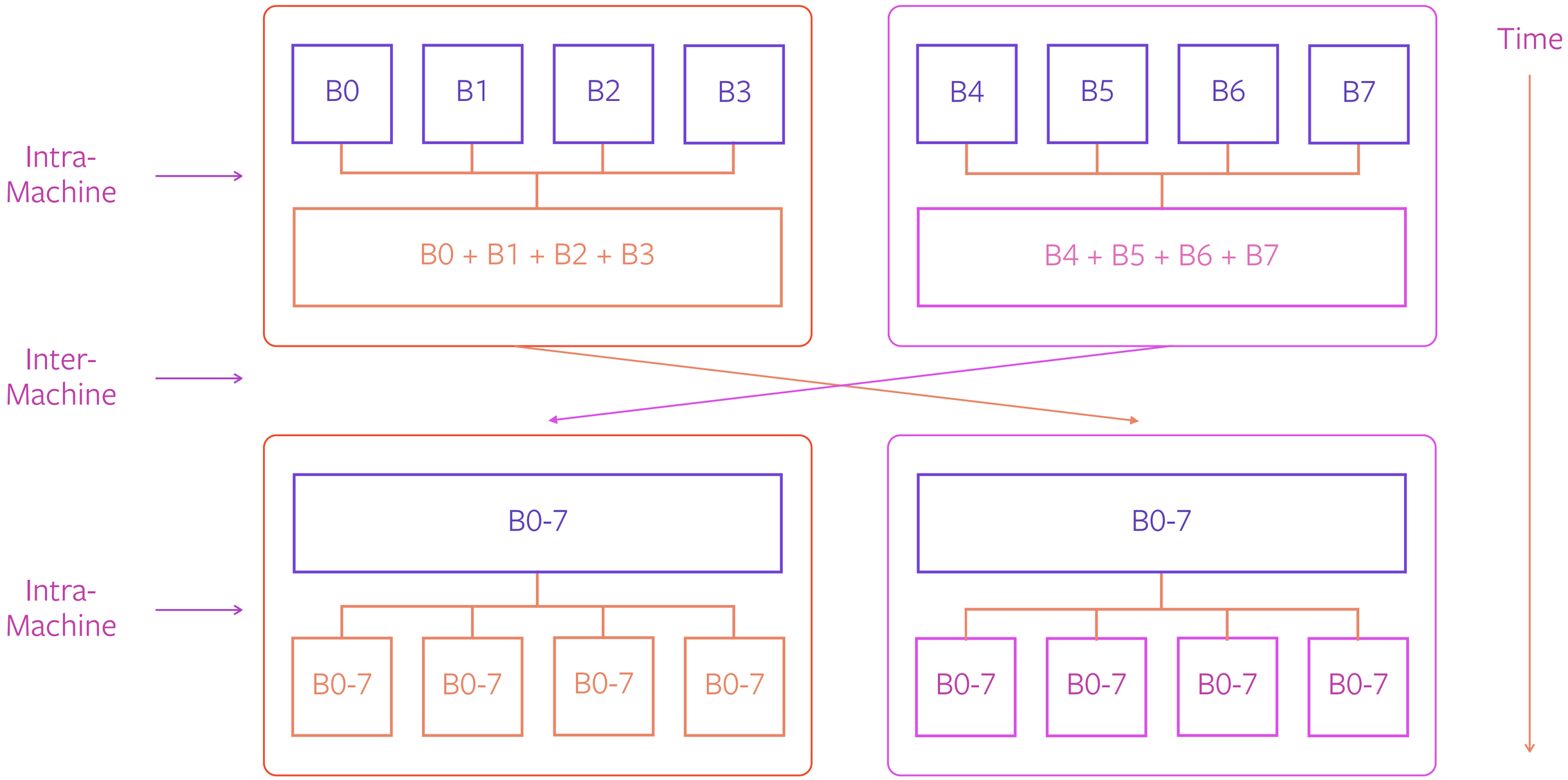


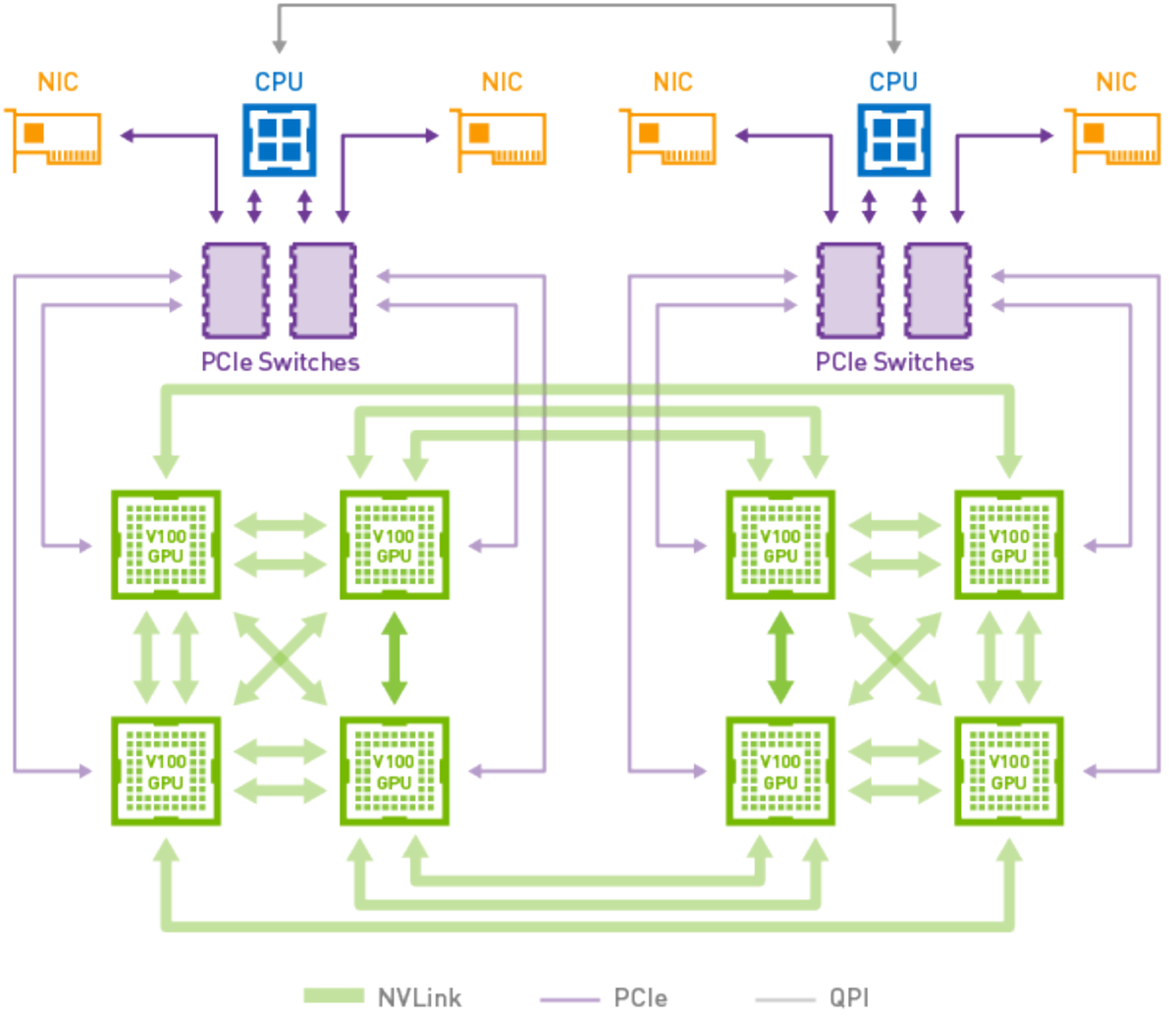

Data parallelism
BACKWARD PASS
W0′ != W1′ != W2′ != WN′
W0′ != W1′ != W2′ != WN′
W0′ != W1′ != W2′ != WN′
LOSS 0
LOSS 1
LOSS 2
LOSS N

Data parallelism

AVERAGE GRADIENTS

The maximum achievable speedup
is determined by the overhead
of the allreduce operation


Intra-
Machine
Inter-
Machine
Intra-
Machine
B0
B1
B2
B3
B0 + B1 + B2 + B3
B4
B5
B6
B7
B4 + B5 + B6 + B7
B0-7
B0-7
B0-7
B0-7
B0-7
B0-7
B0-7
B0-7
B0-7
Time



NVLink connecting eight Tesla V100 accelerators in a hybrid cube mesh topology as used in the DGX-1V server

https://www.nvidia.com/en-us/data-center/nvlink/

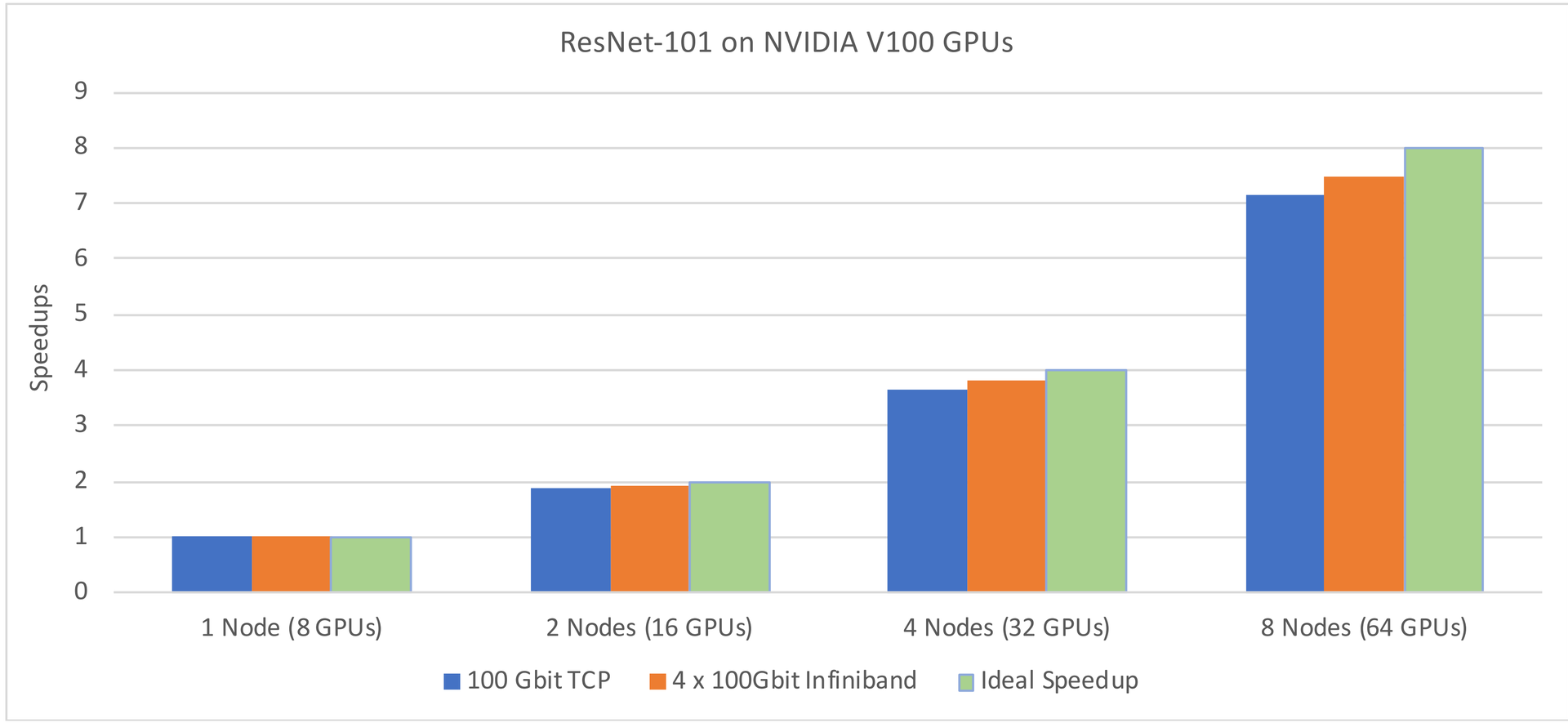
Data parallelism

OVERLAPPING BACKWARD PASS WITH ALLREDUCE

Data parallelism

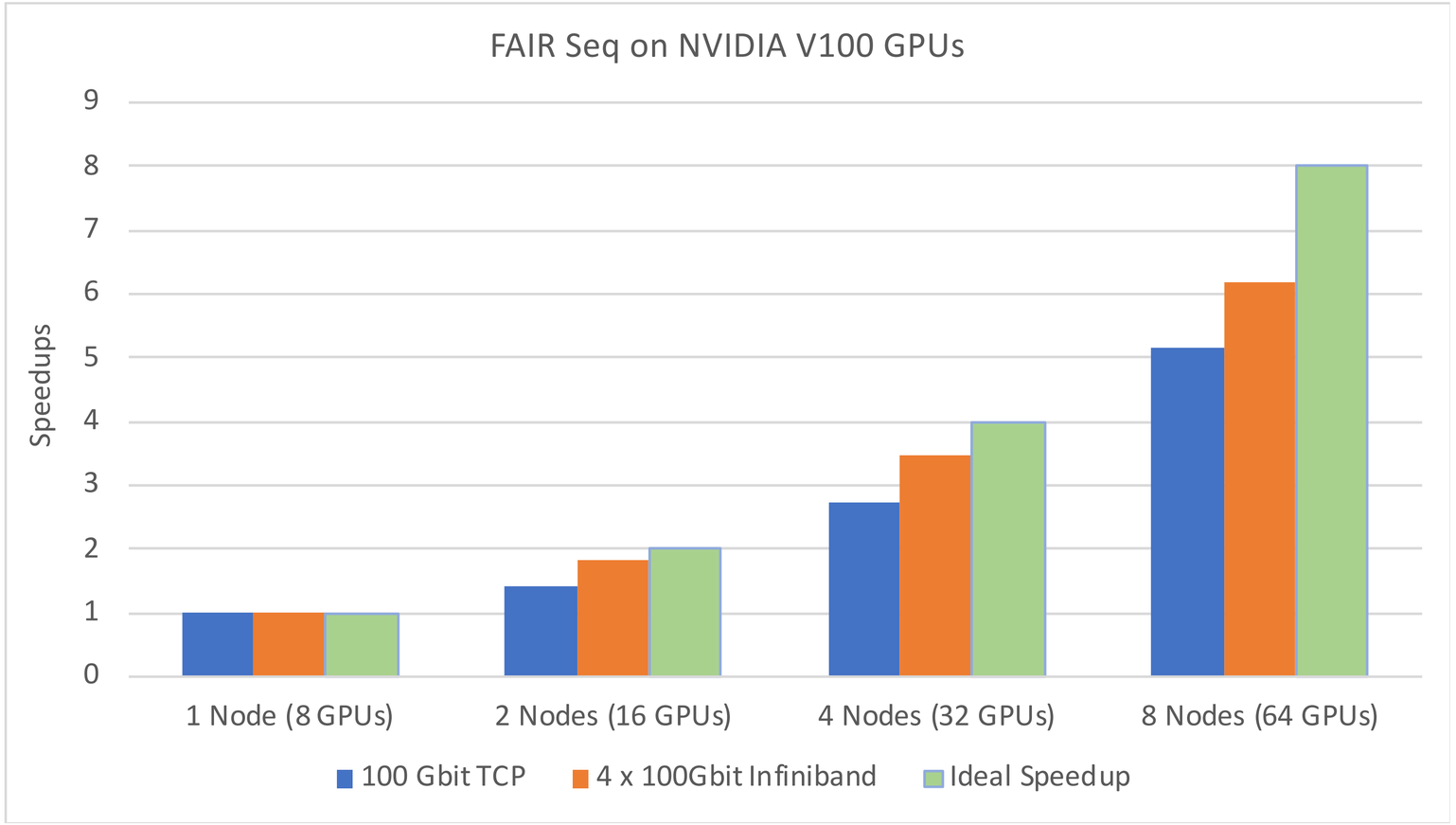
OVERLAPPING BACKWARD PASS WITH ALLREDUCE

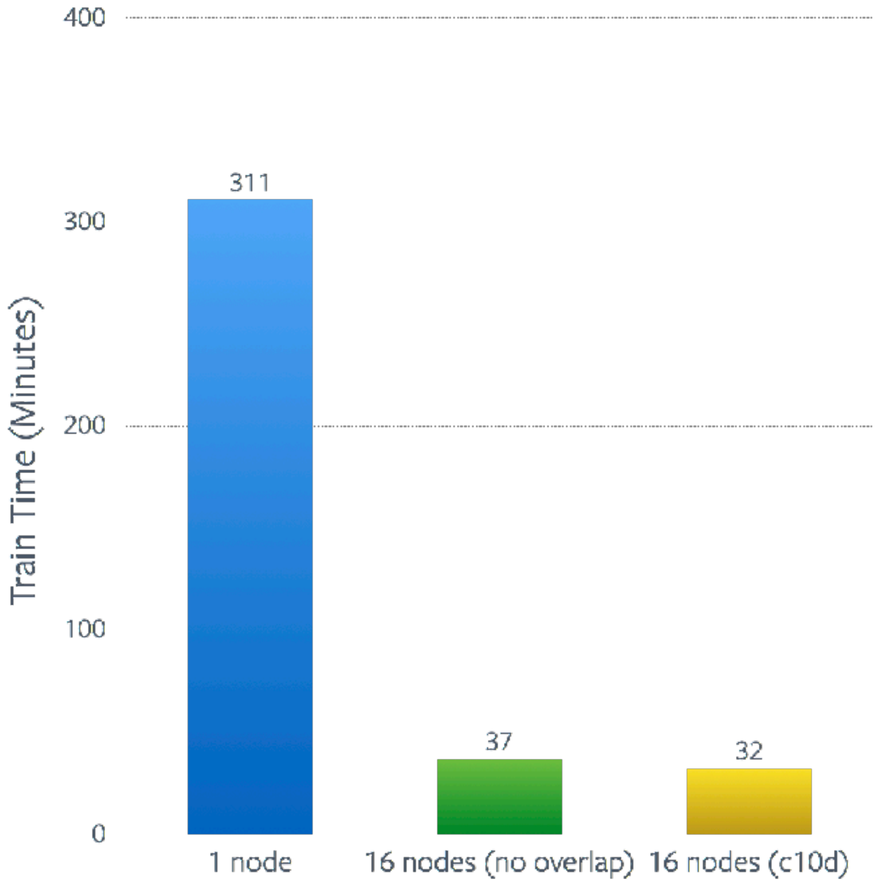
Distributed Training Performance – ResNet101



Distributed Training Performance – FAIR Seq

Bonjour à tous ! → Hello everybody!





- 311 minutes – 32 minutes, by going from 1 to 16 NVIDIA DGX-1 nodes (8 to 128 NVIDIA V100 GPUs)
- 19% performance gain (1.53M – 1.82M Words Per Second on 16 nodes), thanks to c10d DDP overlapping

Data Parallelism API

```
for epoch in range(max_epochs):
  for data, target in enumerate(training_data):
    output = model(data)
    loss = F.nll_loss(output, target)
    loss.backward()
    optimizer.step()
```

Data Parallelism API

```
torch.distributed.init_process_group(world_size=4, init_method='...')
model = torch.nn.DistributedDataParallel(model)

for epoch in range(max_epochs):
  for data, target in enumerate(training_data):
    output = model(data)
    loss = F.nll_loss(output, target)
    loss.backward()
    optimizer.step()
```

PyTorch Ecosystem

PYTORCH ECOSYSTEM

Tools, Libraries and Datasets to enable cutting-edge AI development

PyTorchVision

PyTorchReasoning

PyTorchLanguage

PyTorchSpeech

PyTorch Tools

Ecosystem

- Use the entire Python ecosystem at your will

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- Including SciPy, Scikit-Learn, etc.

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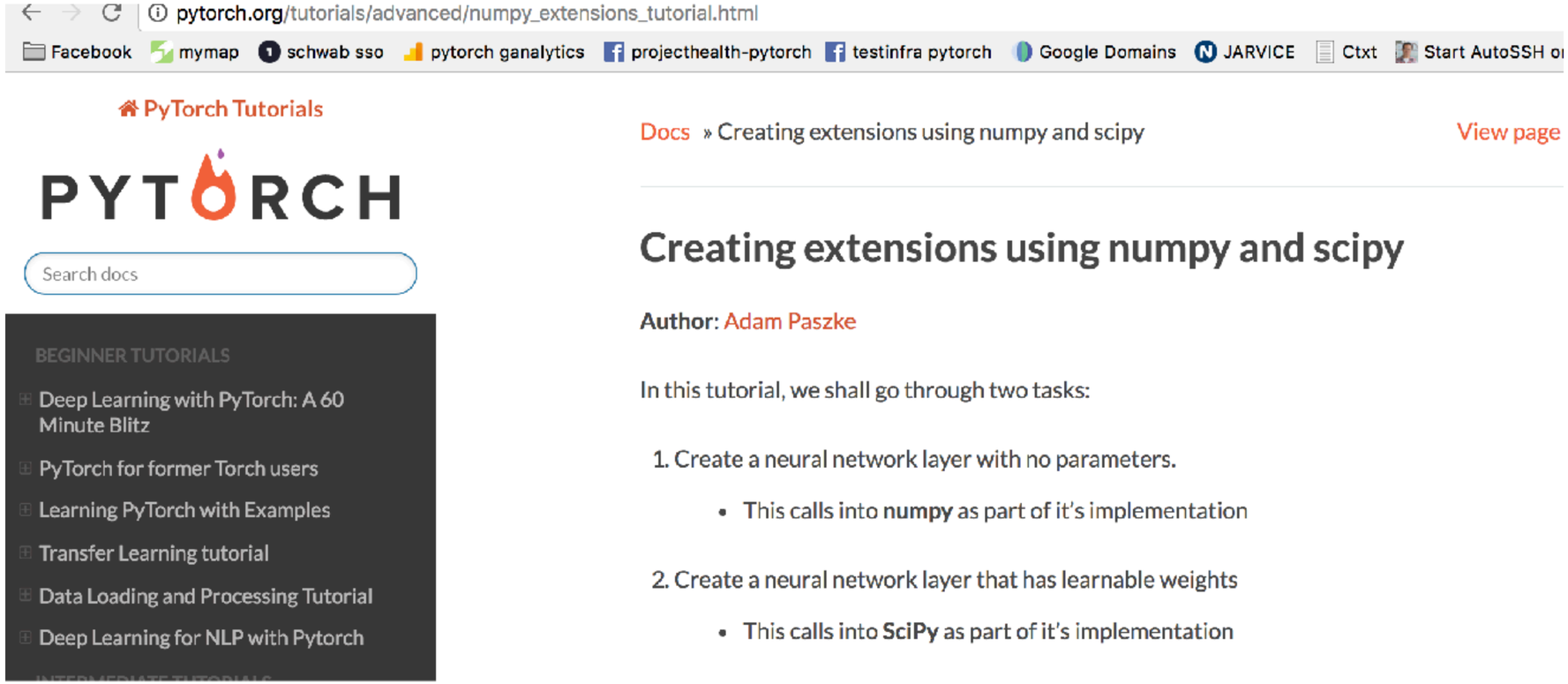


Ecosystem

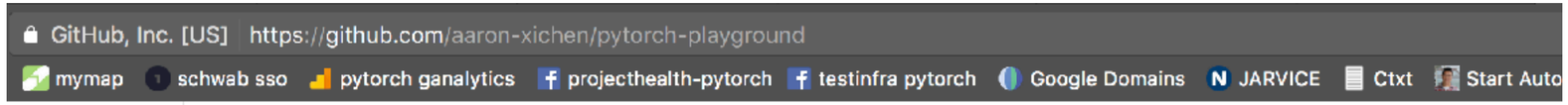
- A shared model-zoo:

We provide pre-trained models for the ResNet variants and AlexNet, using the PyTorch `torch.utils.model_zoo`. These can constructed by passing `pretrained=True`:

```
import torchvision.models as models
resnet18 = models.resnet18(pretrained=True)
alexnet = models.alexnet(pretrained=True)
```

Ecosystem

- A shared



We evaluate the performance of popular dataset and models with linear quantized method. The bit-width of running mean and running variance in BN are 10 bits for all results. (except for 32-float)

Model	32-float	12-bit	10-bit	8-bit	6-bit
MNIST	98.42	98.43	98.44	98.44	98.32
SVHN	96.03	96.03	96.04	96.02	95.46
CIFAR10	93.78	93.79	93.80	93.58	90.86
CIFAR100	74.27	74.21	74.19	73.70	66.32
STL10	77.59	77.65	77.70	77.59	73.40
AlexNet	55.70/78.42	55.66/78.41	55.54/78.39	54.17/77.29	18.19/36.25
VGG16	70.44/89.43	70.45/89.43	70.44/89.33	69.99/89.17	53.33/76.32
VGG19	71.36/89.94	71.35/89.93	71.34/89.88	70.88/89.62	56.00/78.62
ResNet18	68.63/88.31	68.62/88.33	68.49/88.25	66.80/87.20	19.14/36.49
ResNet34	72.50/90.86	72.46/90.82	72.45/90.85	71.47/90.00	32.25/55.71
ResNet50	74.98/92.17	74.94/92.12	74.91/92.09	72.54/90.44	2.43/5.36
ResNet101	76.69/93.30	76.66/93.25	76.22/92.90	65.69/79.54	1.41/1.18
ResNet152	77.55/93.59	77.51/93.62	77.40/93.54	74.95/92.46	9.29/16.75
SqueezeNetV0	56.73/79.39	56.75/79.40	56.70/79.27	53.93/77.04	14.21/29.74
SqueezeNetV1	56.52/79.13	56.52/79.15	56.24/79.03	54.56/77.33	17.10/32.46
InceptionV3	76.41/92.78	76.43/92.71	76.44/92.73	73.67/91.34	1.50/4.82

fast.ai 1.0

High-level library on PyTorch: http://docs.fast.ai

- state-of-the-art models in few lines
- fine-tune on your own data

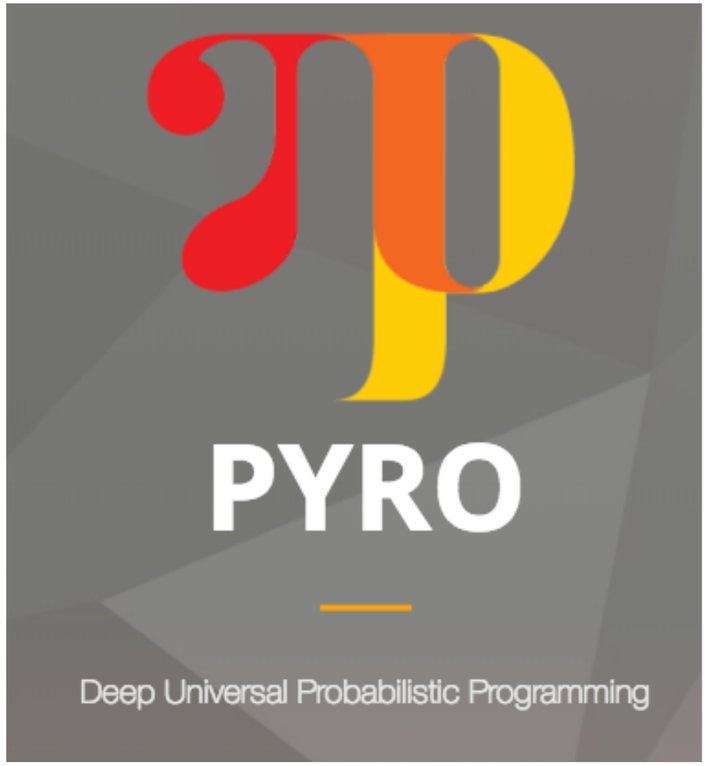
Built by Jeremy Howard, Rachel Thomas and community

+ online course in addition to the library

Read more at http://www.fast.ai/2018/10/02/fastai-ai/

Ecosystem

- Probabilistic Programming



http://pyro.ai/

github.com/probtorch/probtorch

Ecosystem

- Gaussian Processes

GPyTorch (Alpha Relase)

build passing

GPyTorch is a Gaussian Process library, implemented using PyTorch. It is designed for creating flexible and modular Gaussian Process models with ease, so that you don't have to be an expert to use GPs.

This package is currently under development, and is likely to change. Some things you can do right now:

- Simple GP regression (example here)
- Simple GP classification (example here)
- Multitask GP regression (example here)
- Scalable GP regression using kernel interpolation (example here)
- Scalable GP classification using kernel interpolation (example here)
- Deep kernel learning (example here)
- And (more!)

https://github.com/cornellius-gp/gpytorch

Ecosystem

- Machine Translation

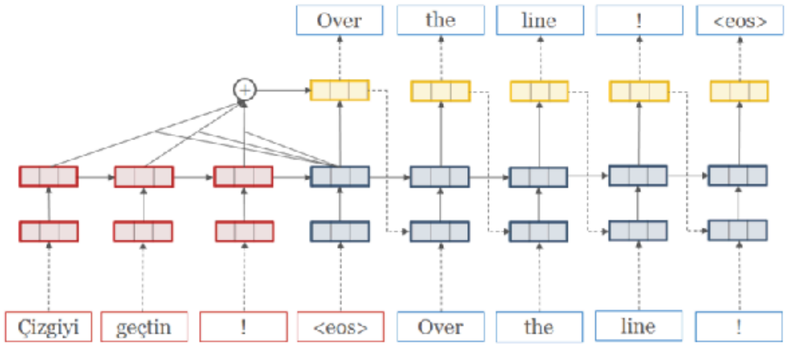
OpenNMT-py: Open-Source Neural Machine Translation

build passing

This is a Pytorch port of OpenNMT, an open-source (MIT) neural machine translation system. It is designed to be research friendly to try out new ideas in translation, summary, image-to-text, morphology, and many other domains.

Codebase is relatively stable, but PyTorch is still evolving. We currently recommend forking if you need to have stable code.

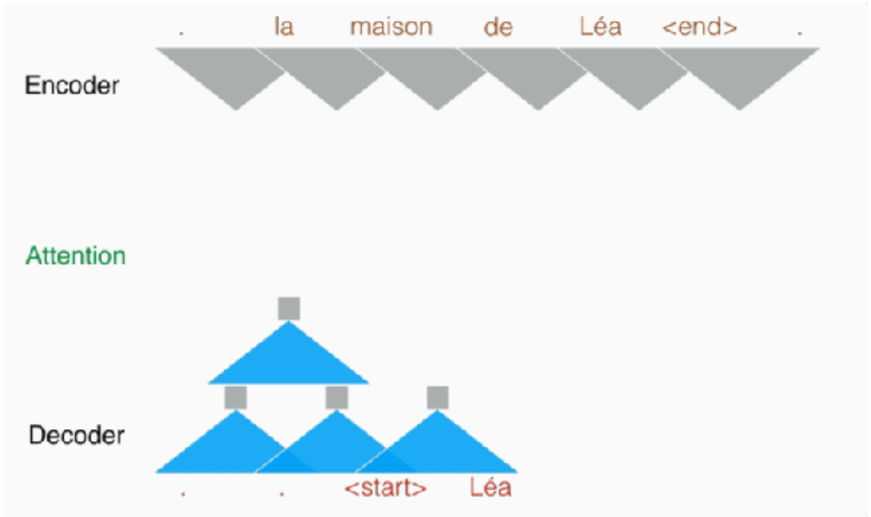
OpenNMT-py is run as a collaborative open-source project. It is maintained by Sasha Rush (Cambridge, MA), Ben Peters (Saarbrücken), and Jianyu Zhan (Shenzhen). The original code was written by Adam Lerer (NYC). We love contributions. Please consult the Issues page for any Contributions Welcome tagged post.



https://github.com/OpenNMT/OpenNMT-py

FAIR Sequence-to-Sequence Toolkit (PyTorch)

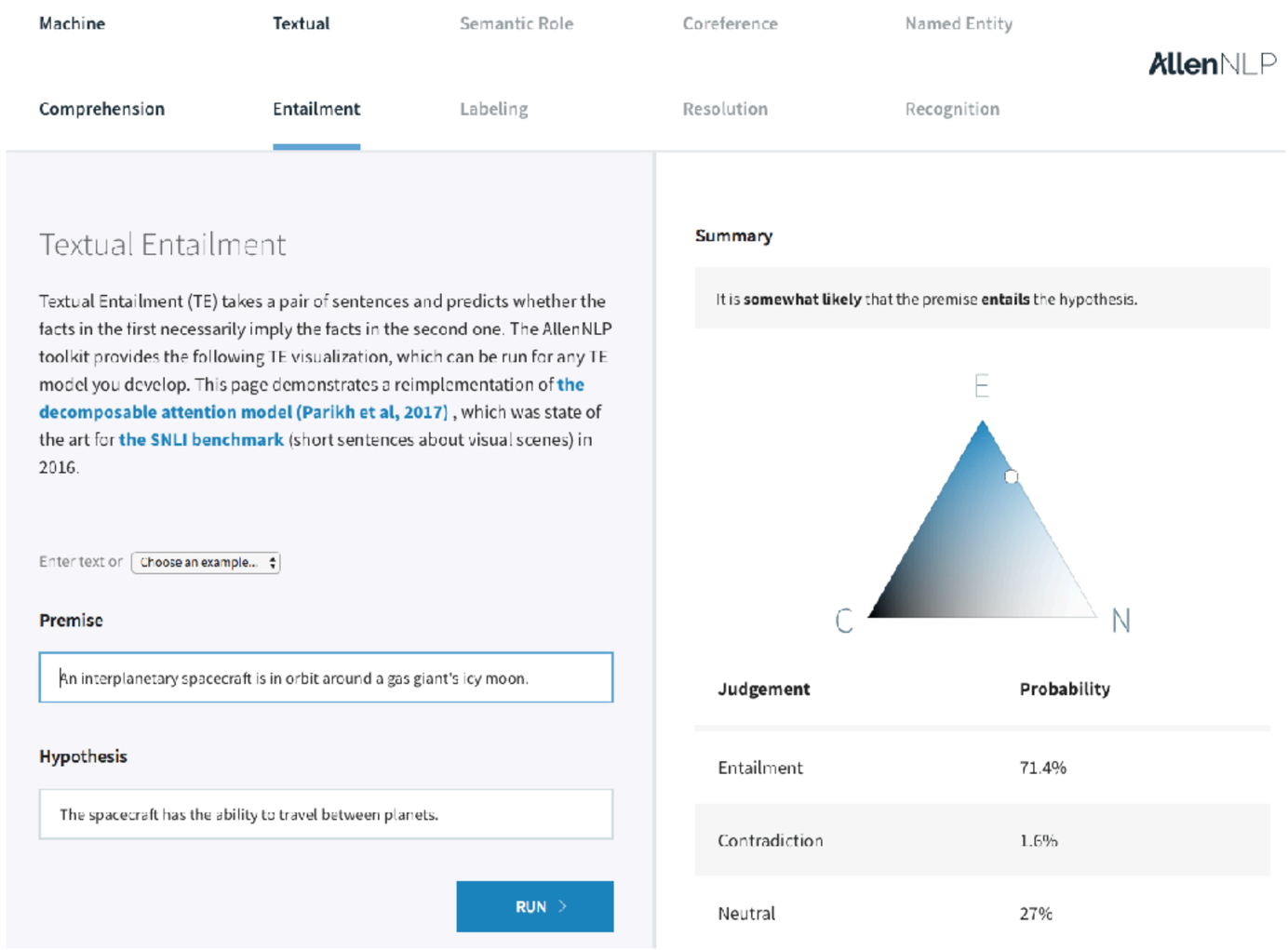
This is a PyTorch version of fairseq, a sequence-to-sequence learning toolkit from Facebook AI Research. The original authors of this reimplementation are (in no particular order) Sergey Edunov, Myle Ott, and Sam Gross. The toolkit implements the fully convolutional model described in Convolutional Sequence to Sequence Learning and features multi-GPU training on a single machine as well as fast beam search generation on both CPU and GPU. We provide pre-trained models for English to French and English to German translation.



https://github.com/facebookresearch/fairseq-py

Ecosystem

- AllenNLP http://allennlp.org/

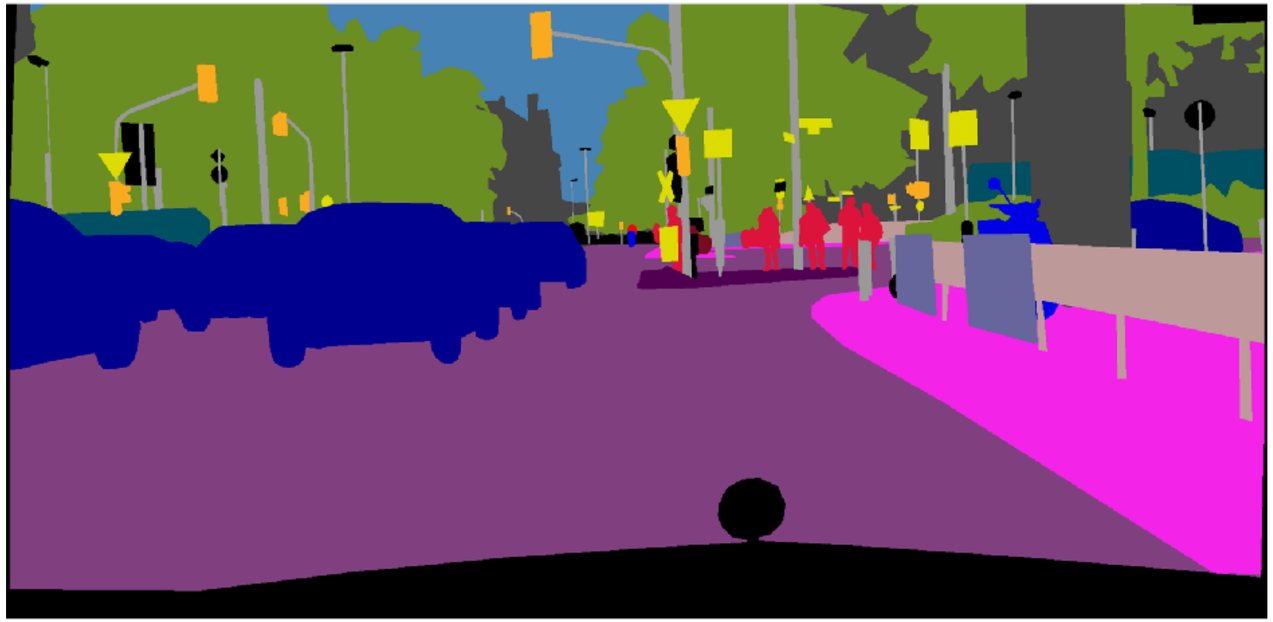


Ecosystem

- Pix2PixHD

https://github.com/NVIDIA/pix2pixHD

Input labels



Synthesized image

Ecosystem

- CycleGAN, pix2pix

  https://github.com/junyanz/pytorch-CycleGAN-and-pix2pix

pytorch.org

PyTorch 1.0

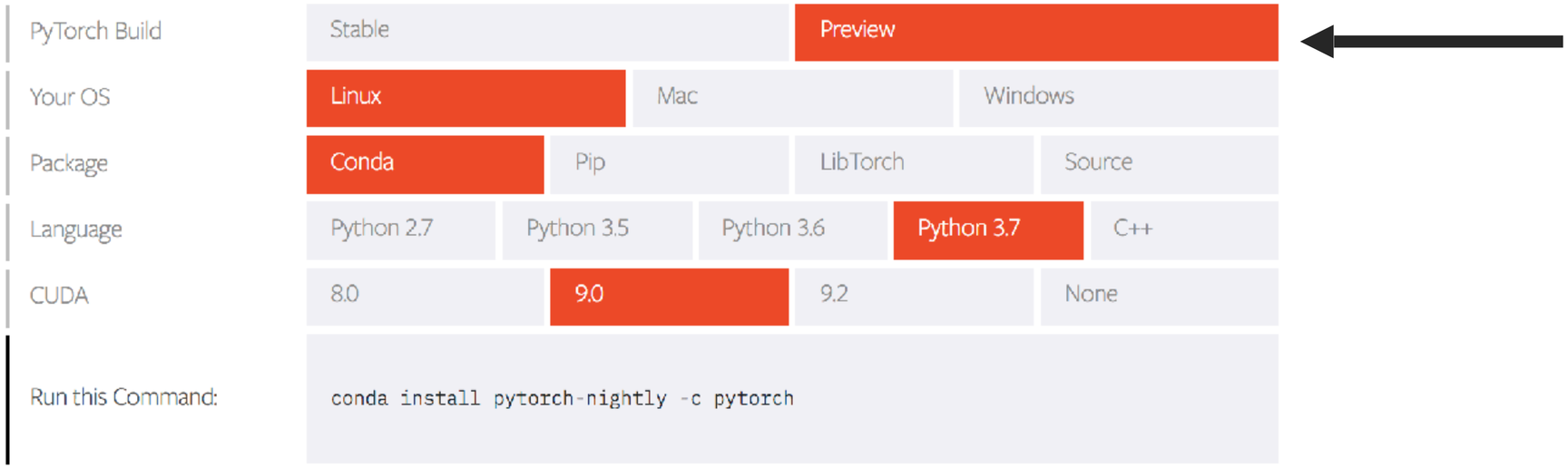
PRODUCTION BATTERIES INCLUDED

PyTorch 1.0

PREVIEW

1.0 PREVIEW

Available on pytorch.org



pytorch.org