
PYTORCH

PYTORCH

a framework for new-generation AI Research

Soumith Chintala, Adam Paszke, Sam Gross & Team

Facebook AI Research

Paradigm shifts in AI research

Today's AI → Active Research & Future AI → Tools for AI *keeping up with change*

PYTORCH

Chainer

mxnet

theano

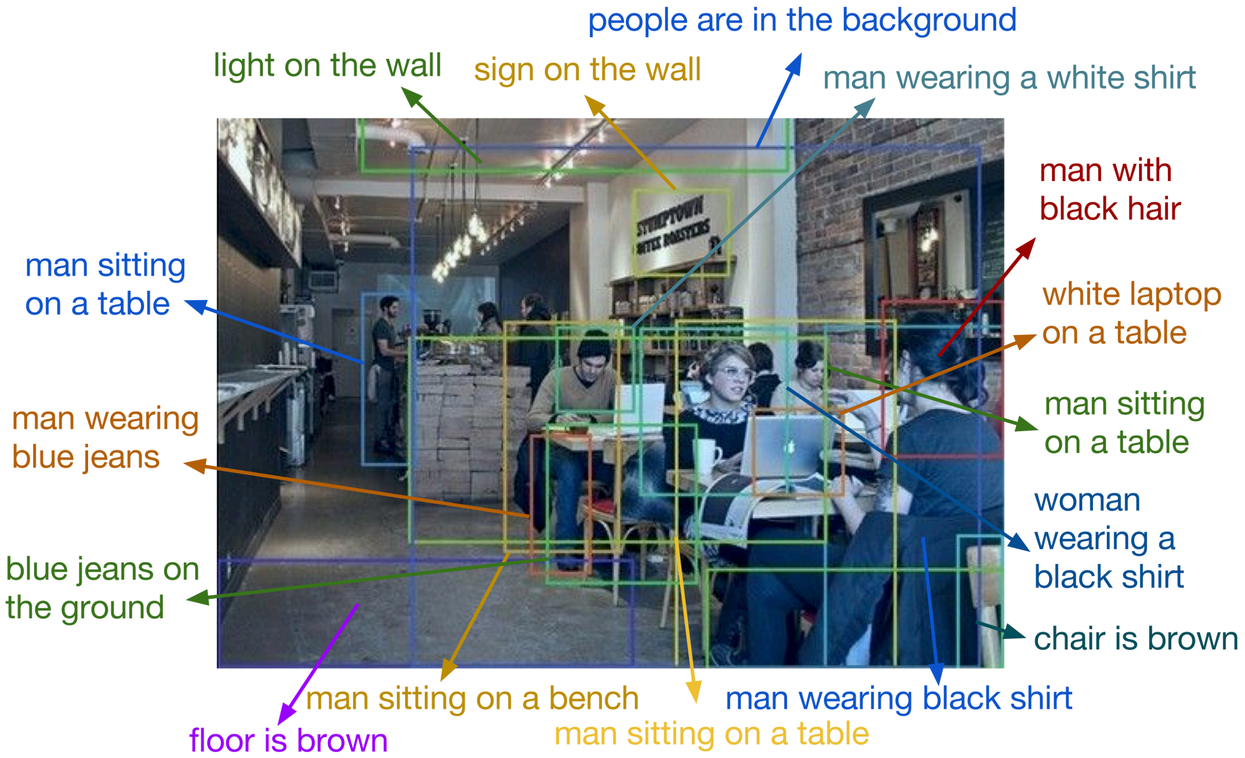
Caffe

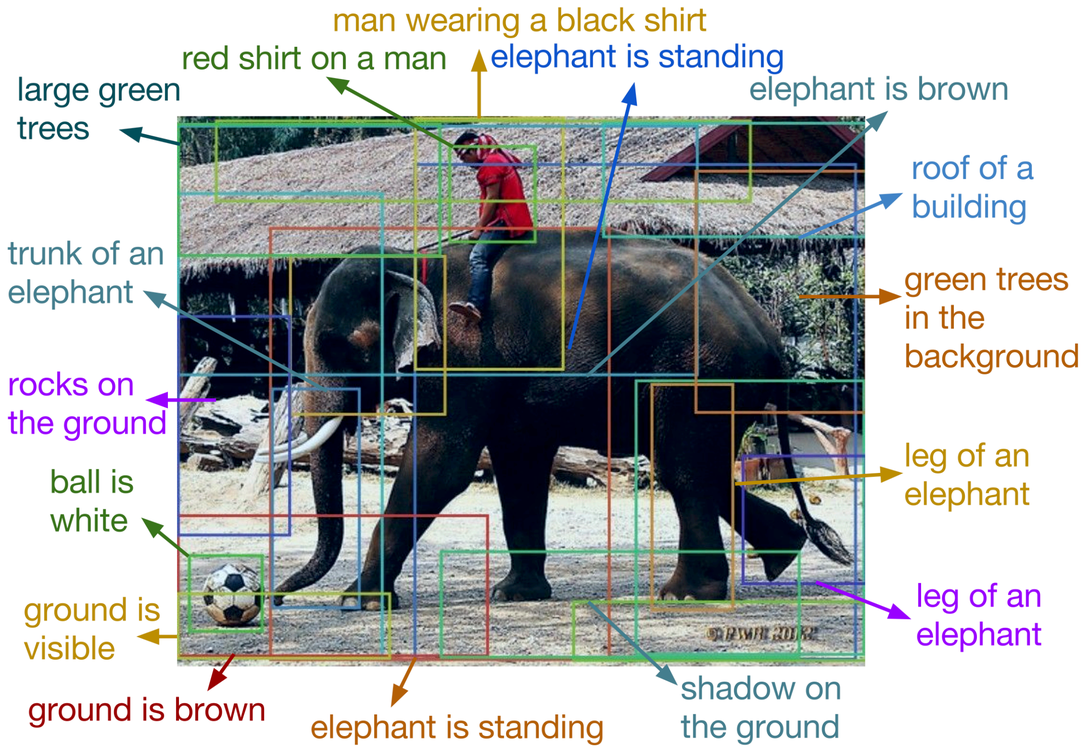
K

Today's AI

DenseCap by Justin Johnson & group

https://github.com/jcjohnson/densecap





Today's AI → Future AI → Tools for AI

Today's AI

DeepMask by Pedro Pinhero & group

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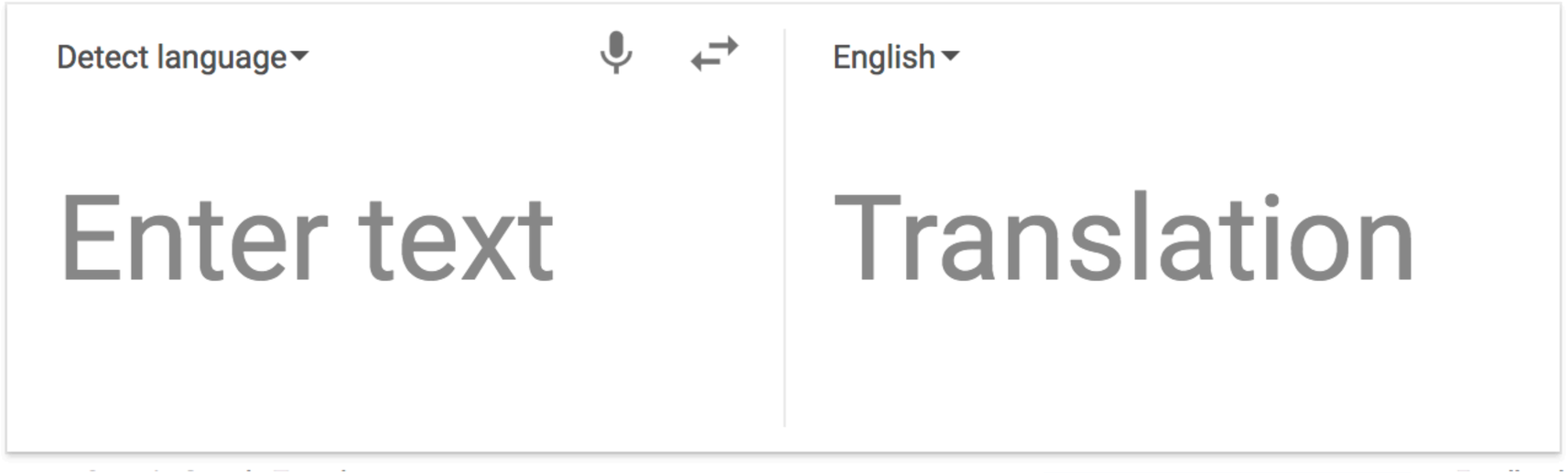
Today's AI

Machine Translation



Google Translate

BING TRANSLATOR

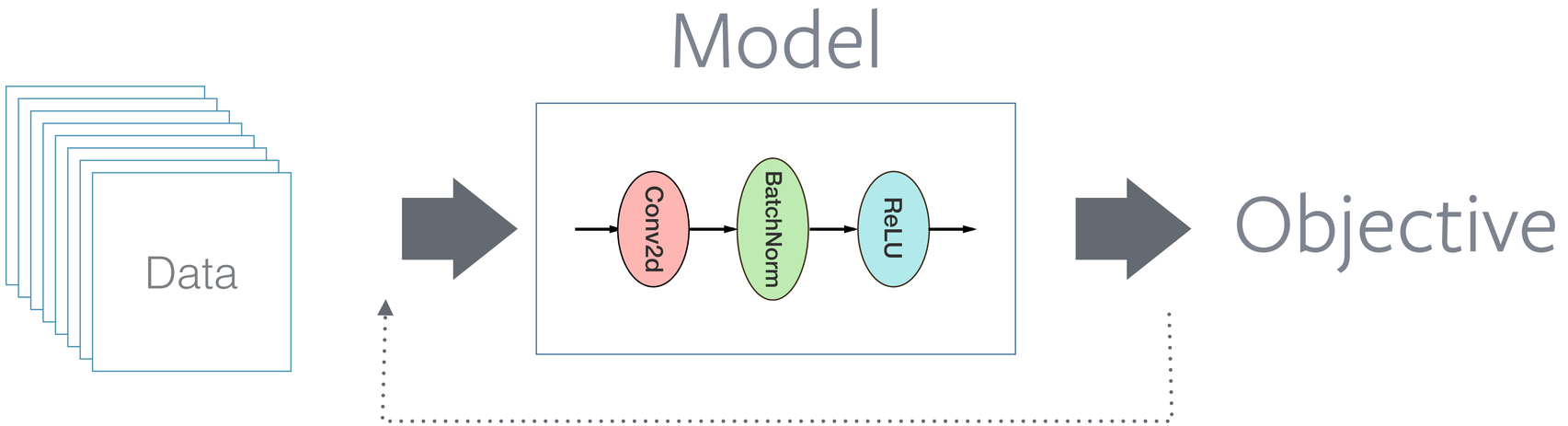
Today's AI → Future AI → Tools for AI

Today's AI

Text Classification (sentiment analysis etc.)
Text Embeddings
Graph embeddings
Machine Translation
Ads ranking

Today's AI

Train Model



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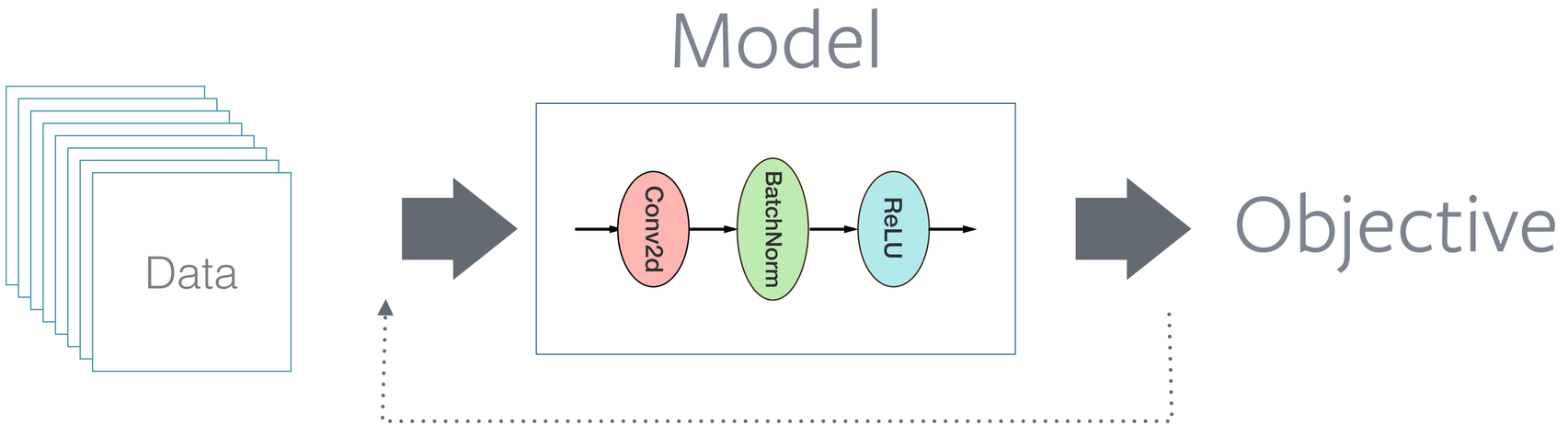
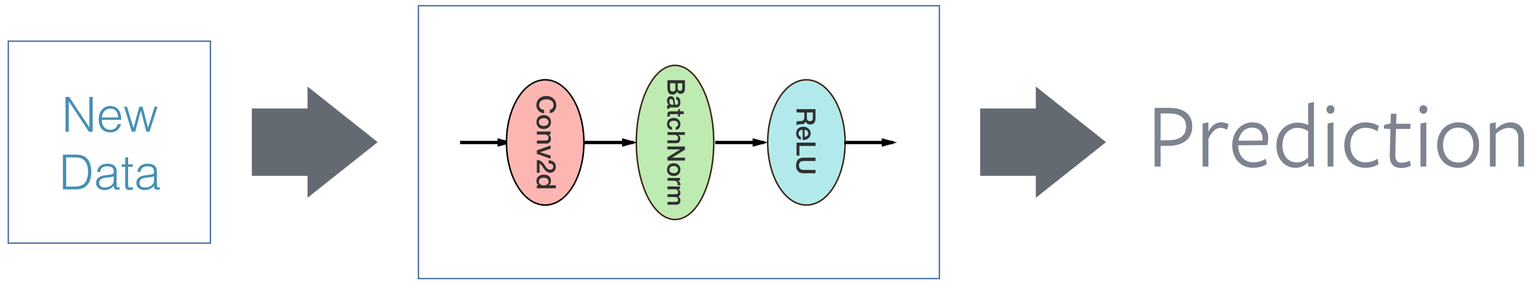
Today's AI

Train Model



Deploy & Use



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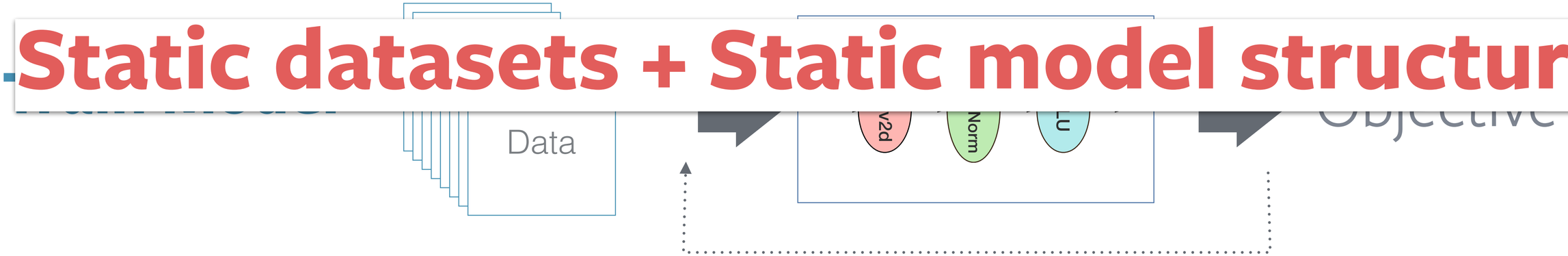
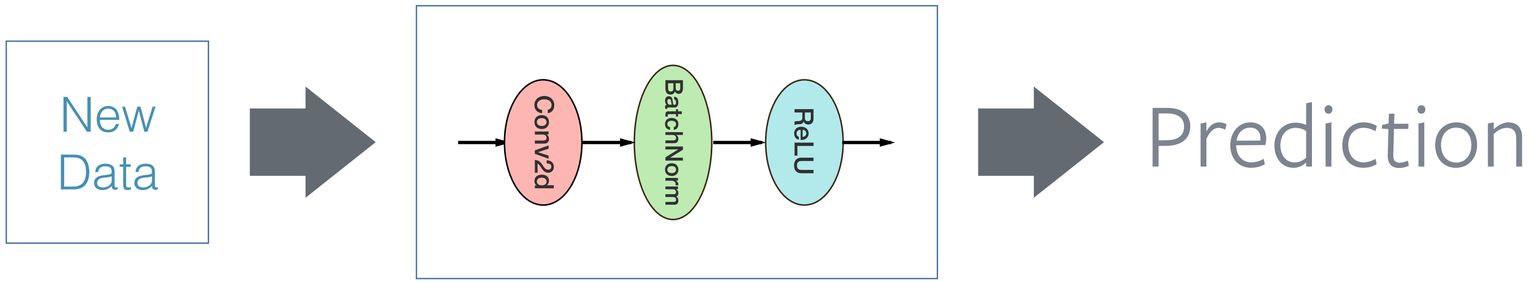
Today's AI

Static datasets + Static model structure



Deploy & Use



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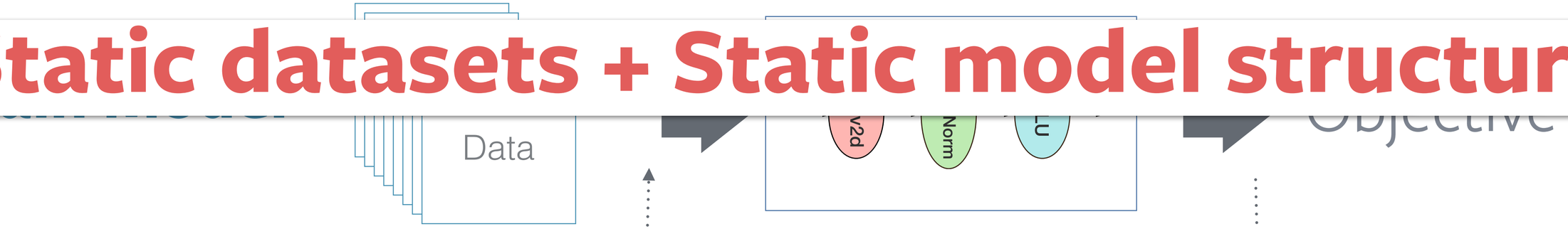
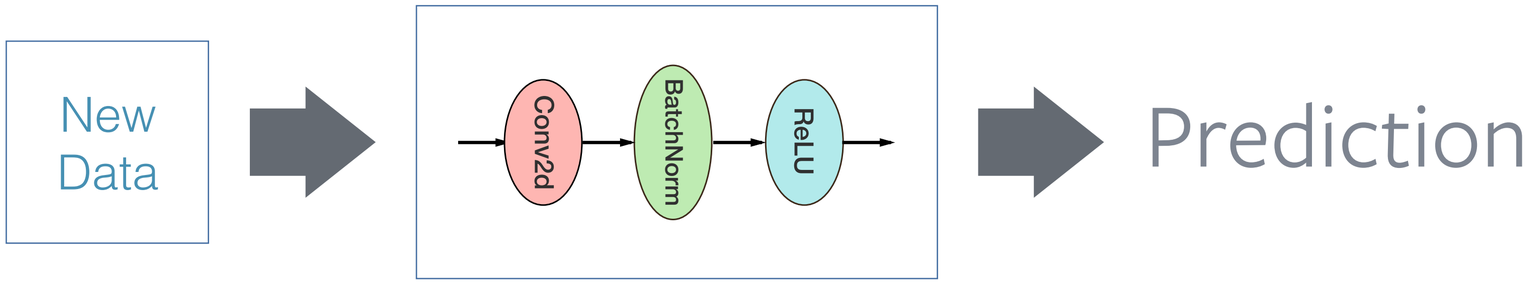
Today's AI

Static datasets + Static model structure



Offline Learning

Deploy & Use



Today's AI → Future AI → Tools for AI

Current AI Research / Future AI

Self-driving Cars

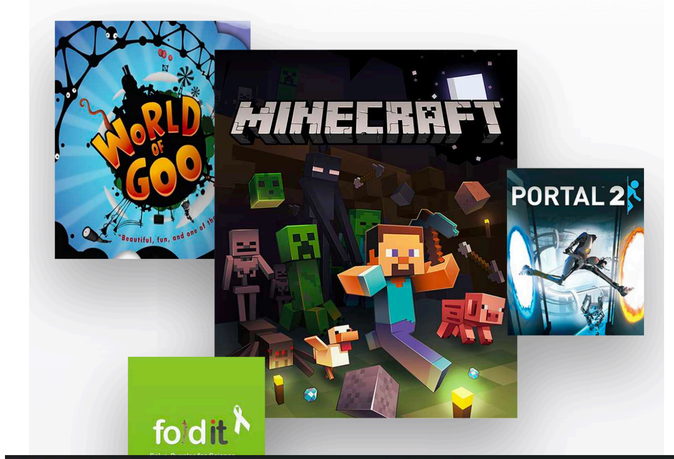
Today's AI → **Future AI** → Tools for AI

Current AI Research / Future AI

Agents trained in many environments

Cars

Video games



Internet

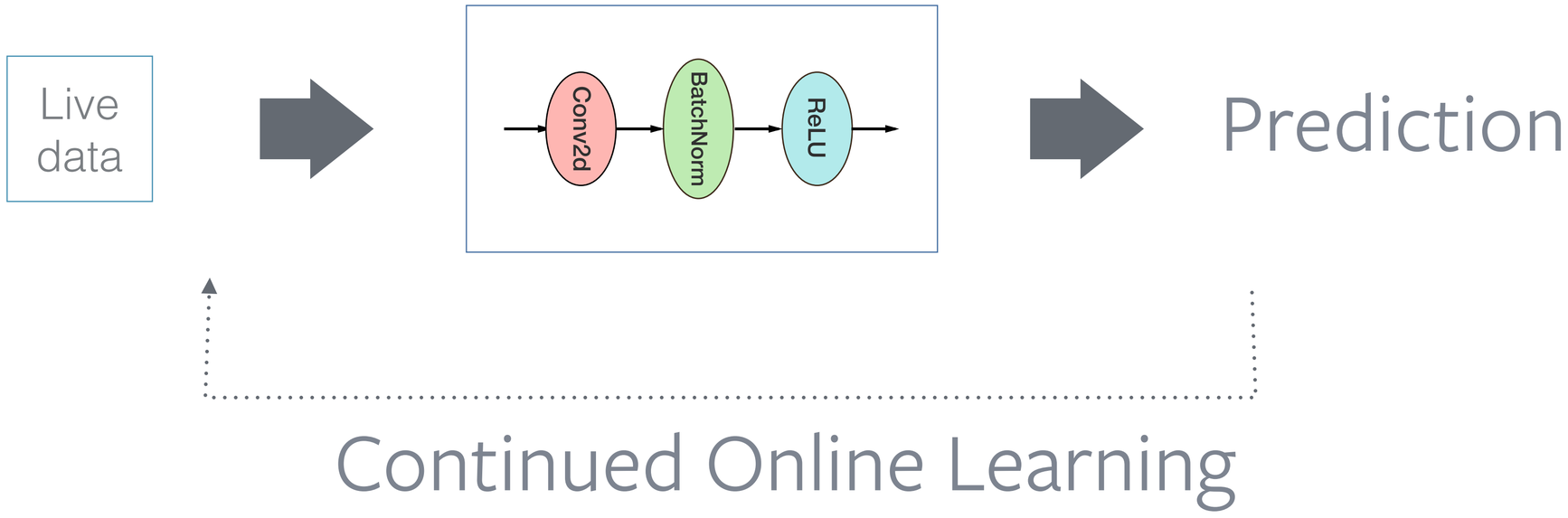
Today's AI → Future AI → Tools for AI

Current AI Research / Future AI

Dynamic Neural Networks

self-adding new memory or layers
changing evaluation path based on inputs

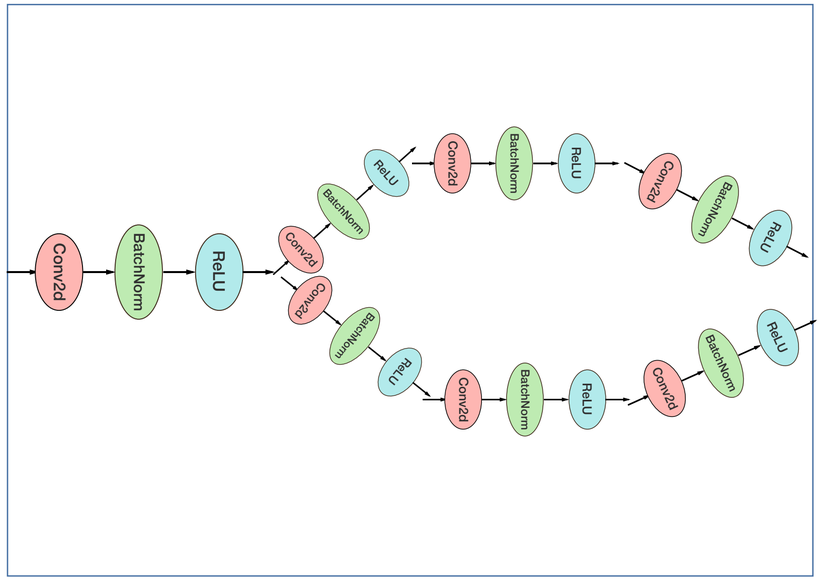
Current AI Research / Future AI



Today's AI → Future AI → Tools for AI

Current AI Research / Future AI

Sample-**1**



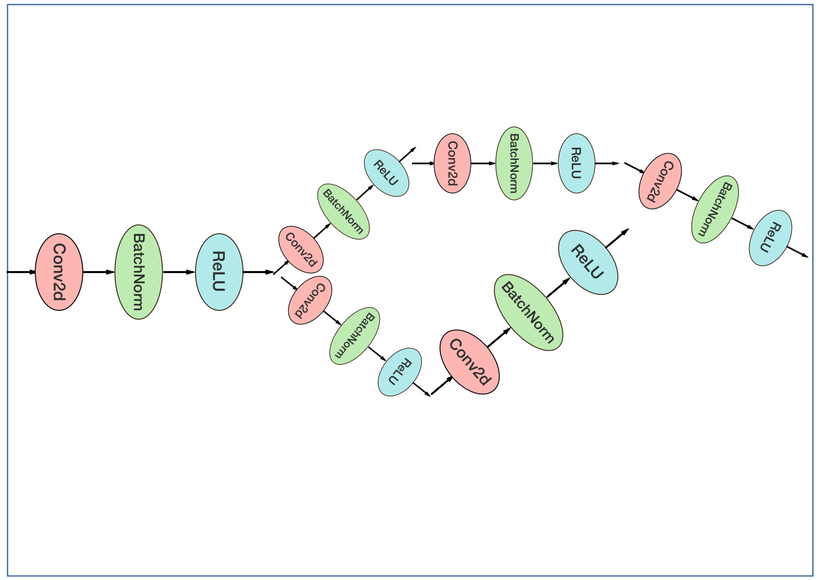
Prediction

Data-dependent change in model structure

Today's AI → **Future AI** → Tools for AI

Current AI Research / Future AI

Sample-**2**

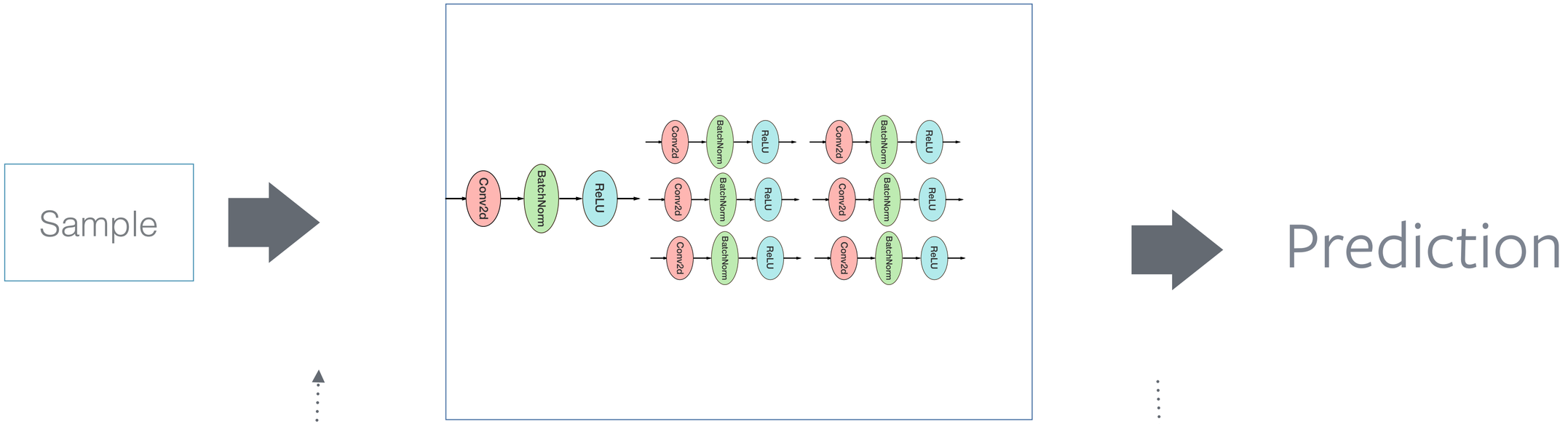


Prediction

Data-dependent change in model structure

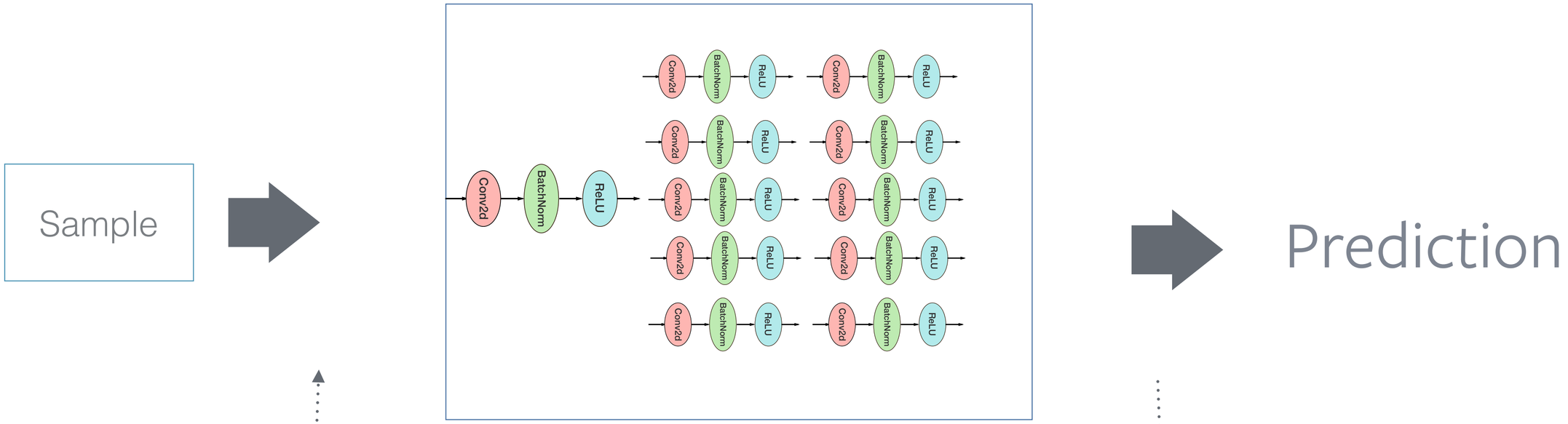
Today's AI → **Future AI** → Tools for AI

Current AI Research / Future AI



Today's AI → Future AI → Tools for AI

Current AI Research / Future AI



Today's AI → Future AI → Tools for AI

The need for a dynamic framework

- Interop with many dynamic environments
  - Connecting to car sensors should be as easy as training on a dataset
  - Connect to environments such as OpenAI Universe
- Dynamic Neural Networks
  - Change behavior and structure of neural network at runtime
- Minimal Abstractions
  - more complex AI systems means harder to debug without a simple API

Tools for AI research and deployment

Many machine learning tools and deep learning frameworks

Today's AI → Future AI → Tools for AI

Tools for AI research and deployment

Static graph frameworks

define-by-run

theano

Caffe

Microsoft CNTK

Dynamic graph frameworks

define-and-run

DyNet

Today's AI → Future AI → Tools for AI

Dynamic graph Frameworks

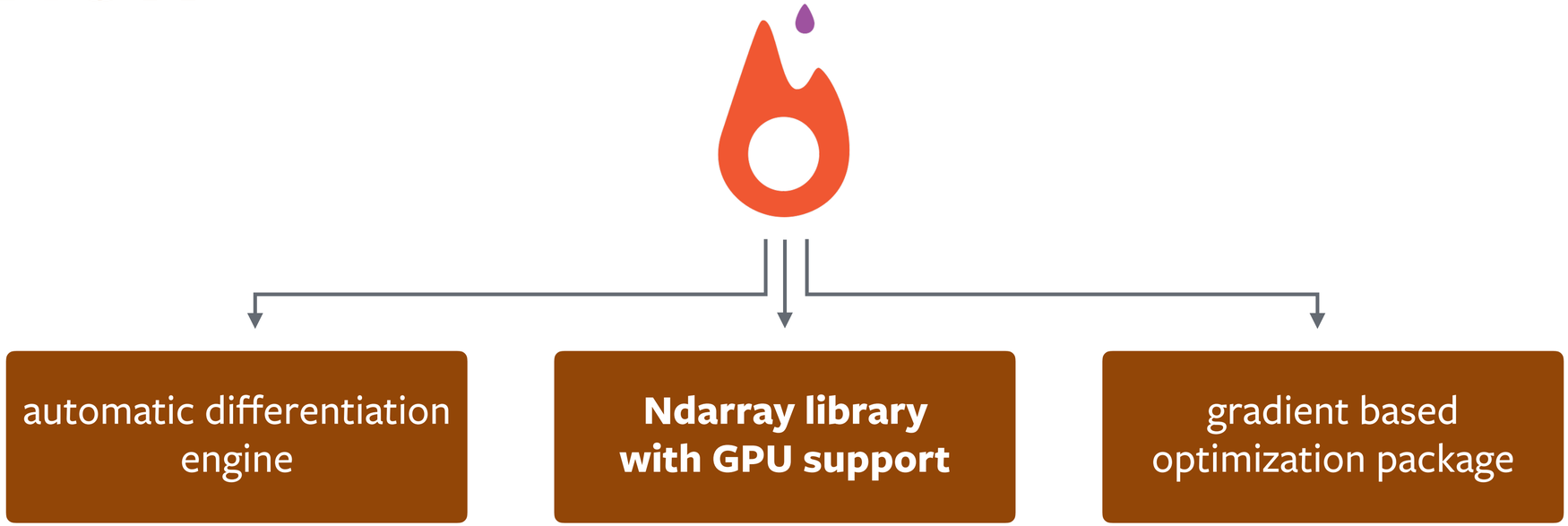
- Model is constructed on the fly at runtime
- Change behavior, structure of model
- Imperative style of programming

DyNet

Today's AI → Future AI → Tools for AI


PYTORCH

Overview



Deep Learning

Reinforcement Learning

Numpy-alternative

ndarray library

with GPU support

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
```

Numpy

```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
```

PyTorch

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]
```

ndarray / Tensor library

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

Out:

```
0.7931  1.1872  1.6143
 1.1946  0.4669  0.9639
 0.7576  0.8136  1.1897
 0.7431  1.8579  1.3400
 0.8188  1.1041  0.8914
[torch.FloatTensor of size 5x3]
```

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
```

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
```

A full suite of high performance
Tensor operations on GPU

GPUs are fast

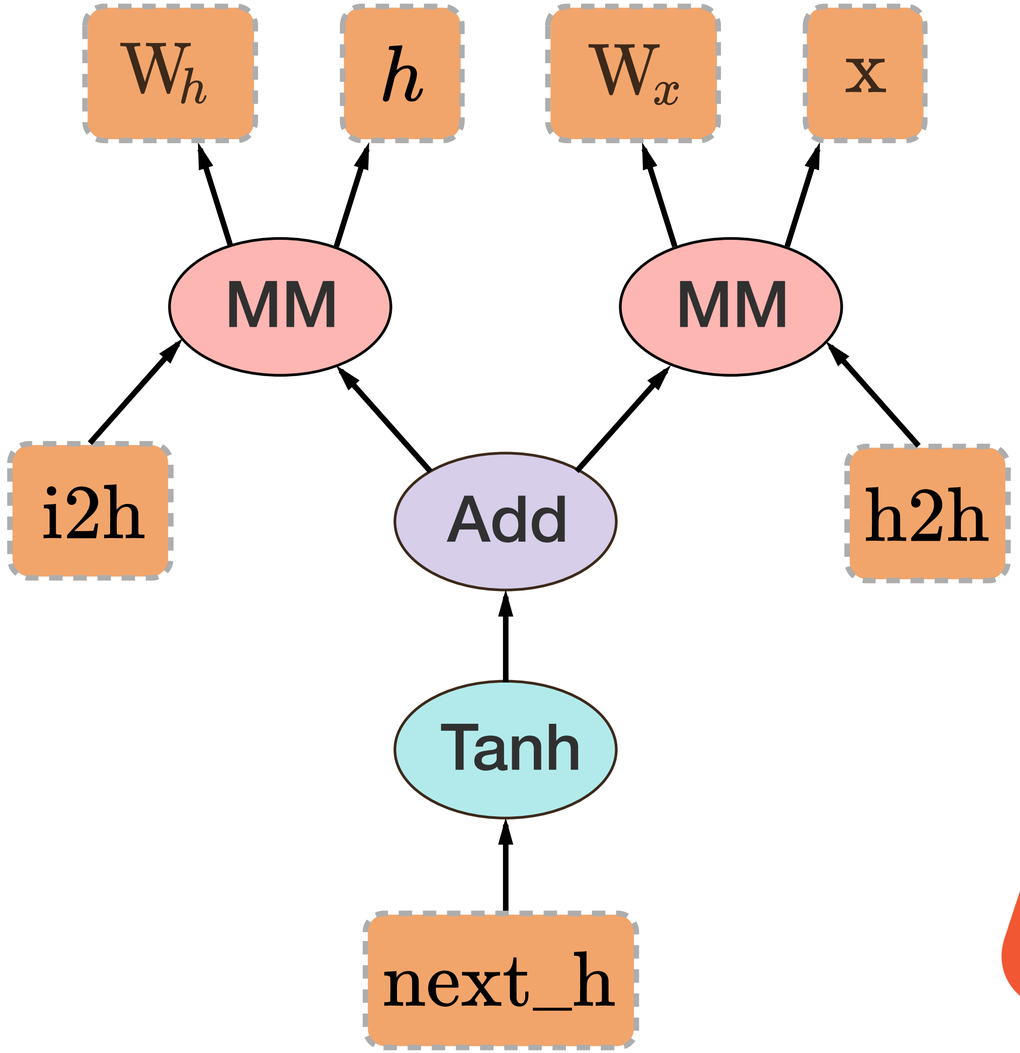
- Buy $700 NVIDIA 1080Ti
- 100x faster matrix multiply
- 10x faster operations in general on matrices

automatic differentiation engine

for deep learning and reinforcement learning

Deep Learning Frameworks

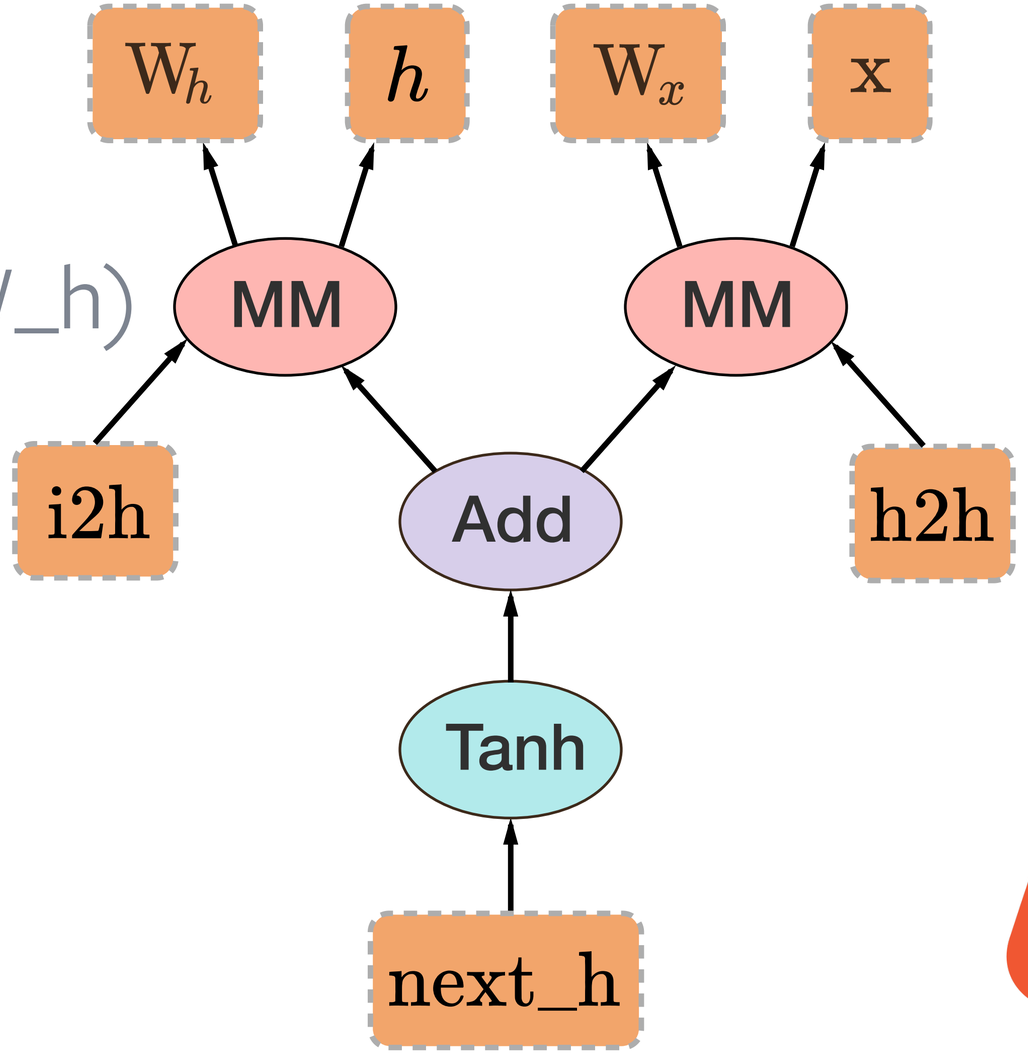
- Provide gradient computation
  - Gradient of one variable w.r.t. any variable in graph



Deep Learning Frameworks

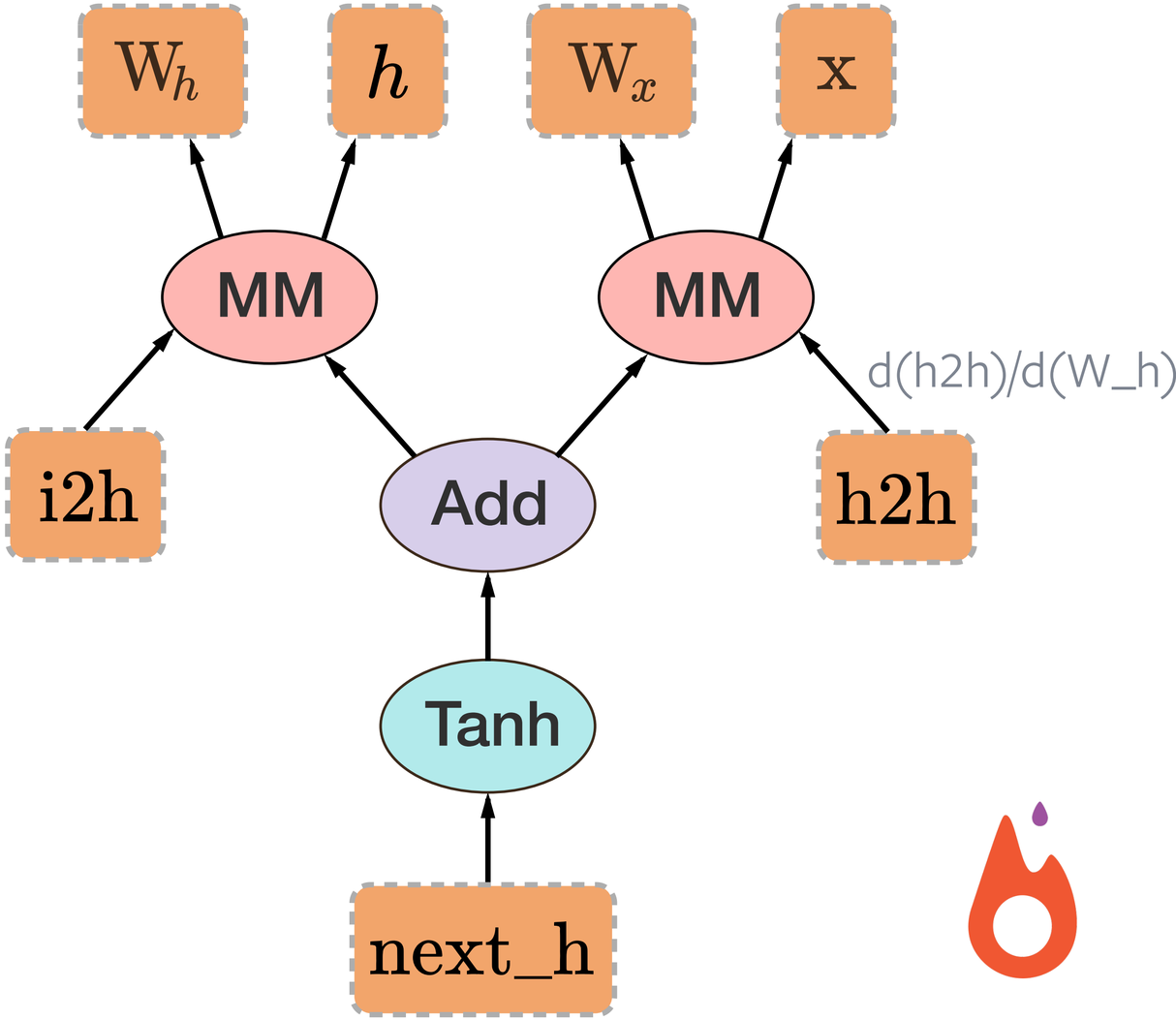
- Provide gradient computation
  - Gradient of one variable w.r.t. any variable in graph

d(i2h)/d(W_h)



Deep Learning Frameworks

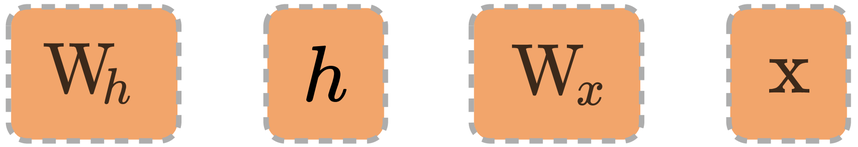
- Provide gradient computation
  - Gradient of one variable w.r.t. any variable in graph
- Provide integration with high performance DL libraries like CuDNN



PyTorch Autograd

```
from torch.autograd import Variable
```

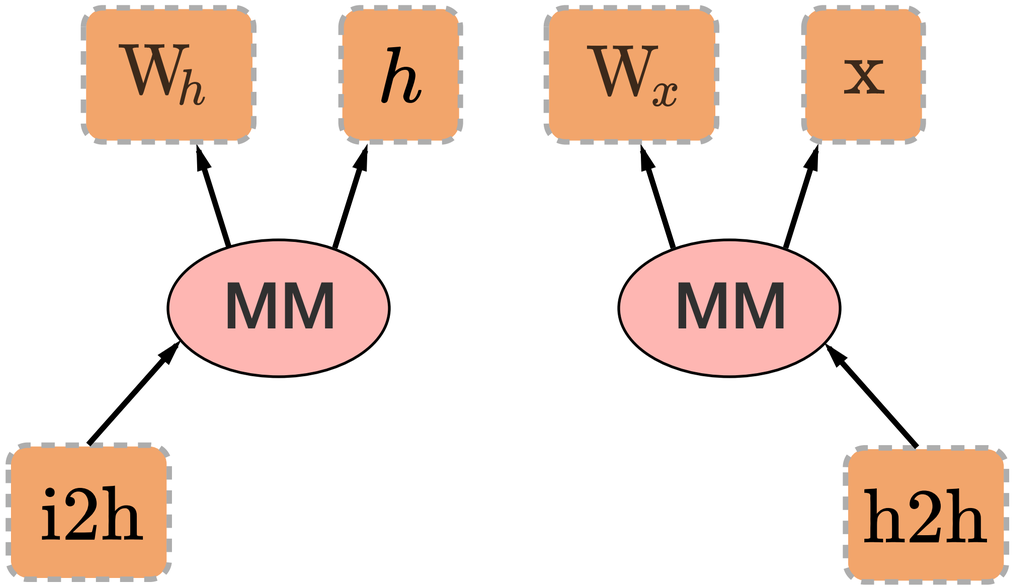
PyTorch Autograd




```
from torch.autograd import Variable

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

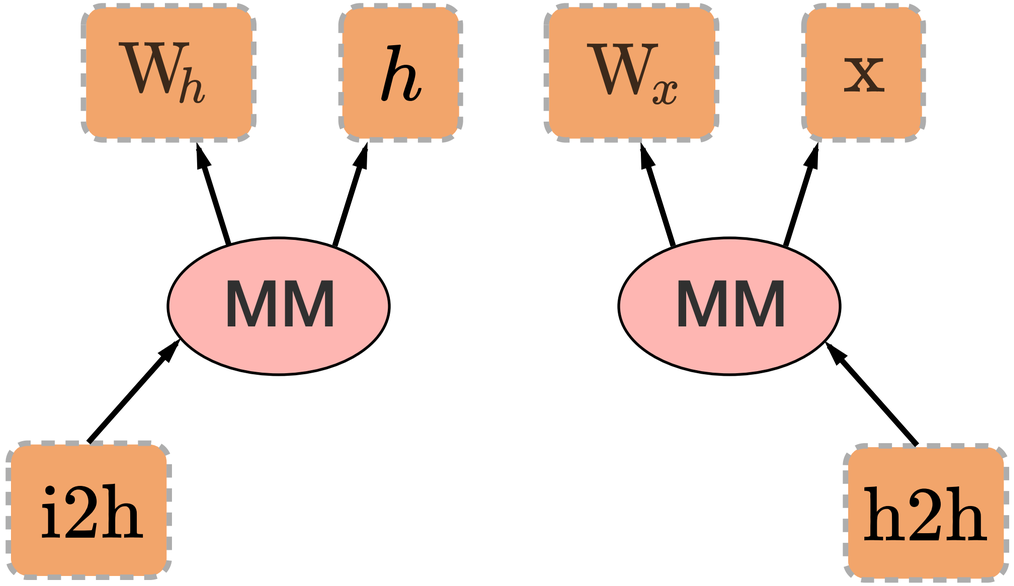
PyTorch Autograd

```
from torch.autograd import Variable

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

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



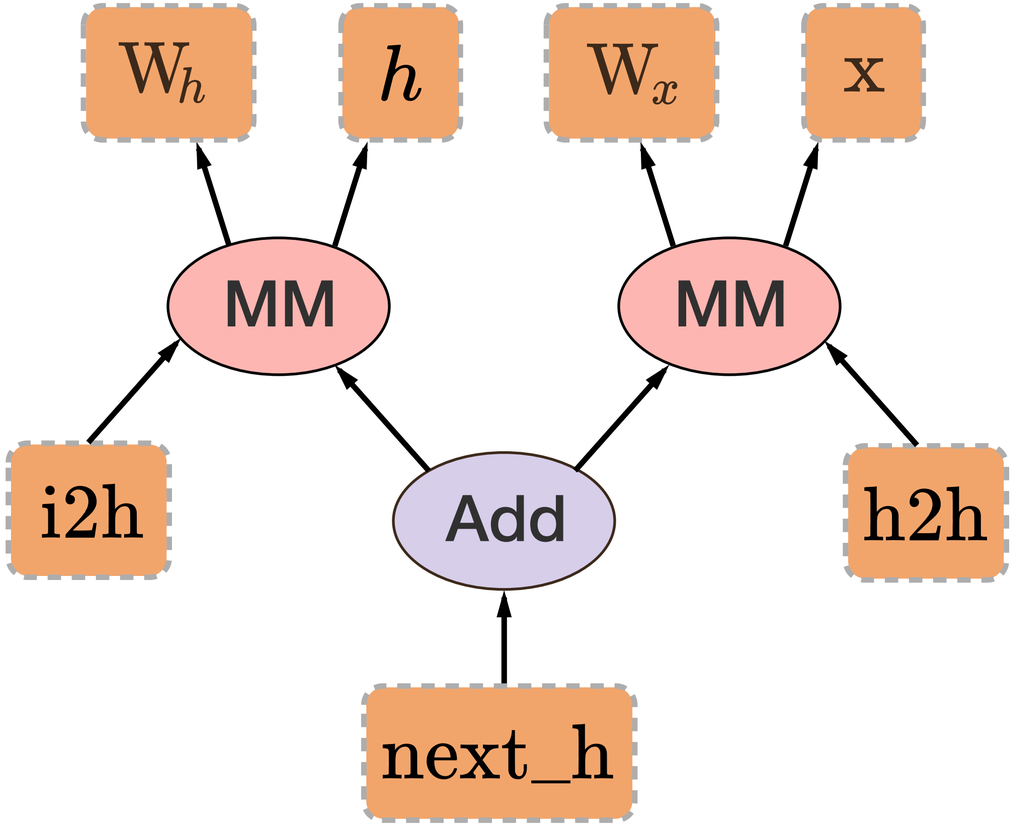
PyTorch Autograd

```
from torch.autograd import Variable

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

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



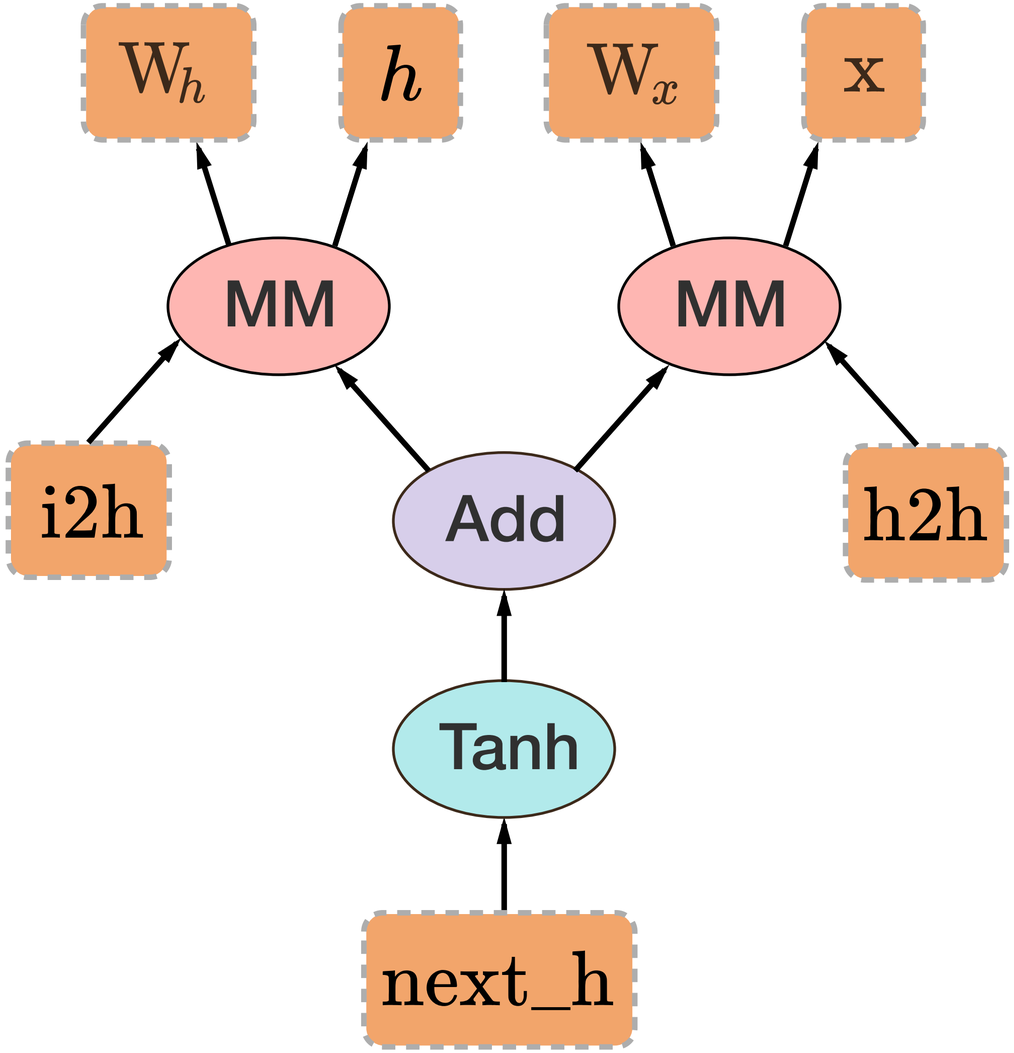
PyTorch Autograd

```
from torch.autograd import Variable

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

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



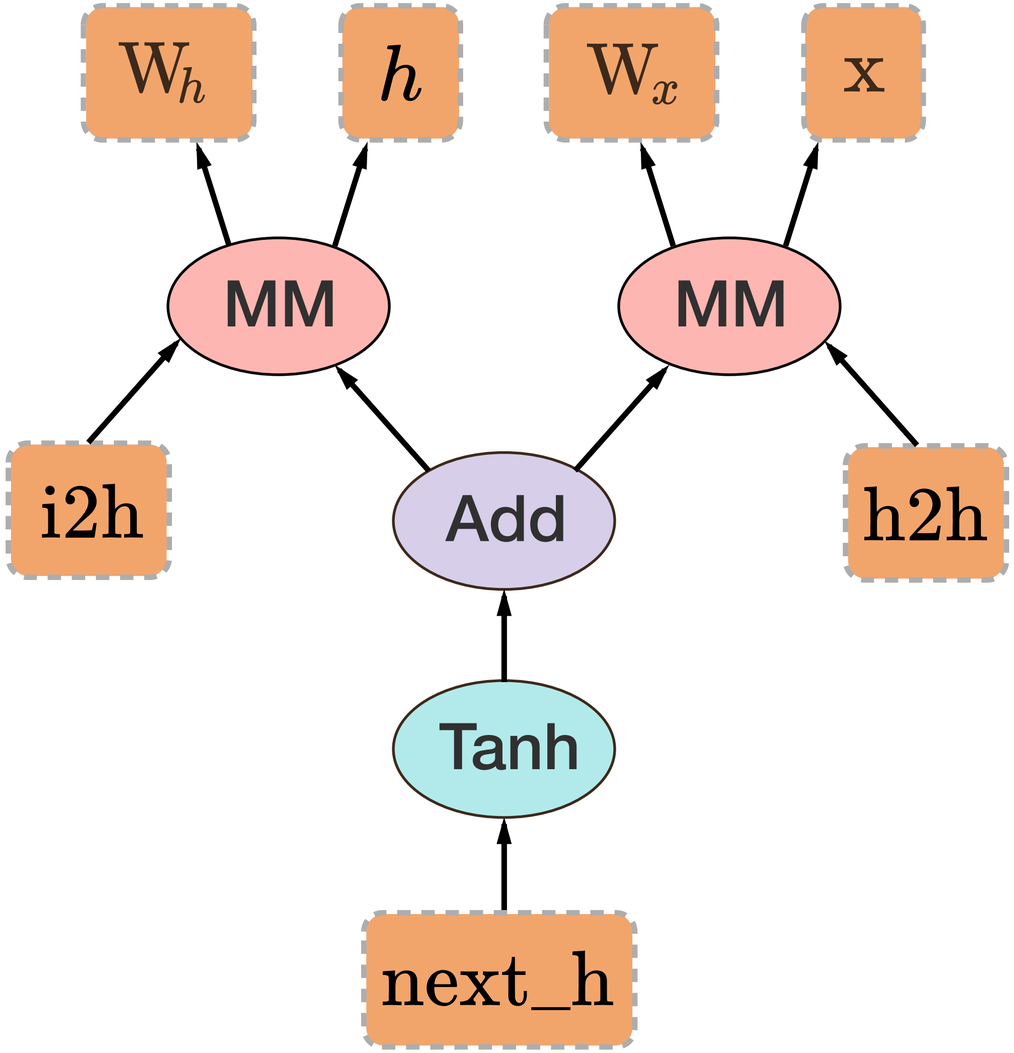
PyTorch Autograd

```
from torch.autograd import Variable

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

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

```
from torch.autograd import Variable

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

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))
```



side by side: TensorFlow and PyTorch

```python
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))
```

```python
import torch
from torch.autograd import Variable

trX = torch.linspace(-1, 1, 101)
trY = 2 * trX + torch.randn(*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)

    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)
```

High performance

- Integration of:
  - CuDNN v6
  - NCCL
  - Intel MKL

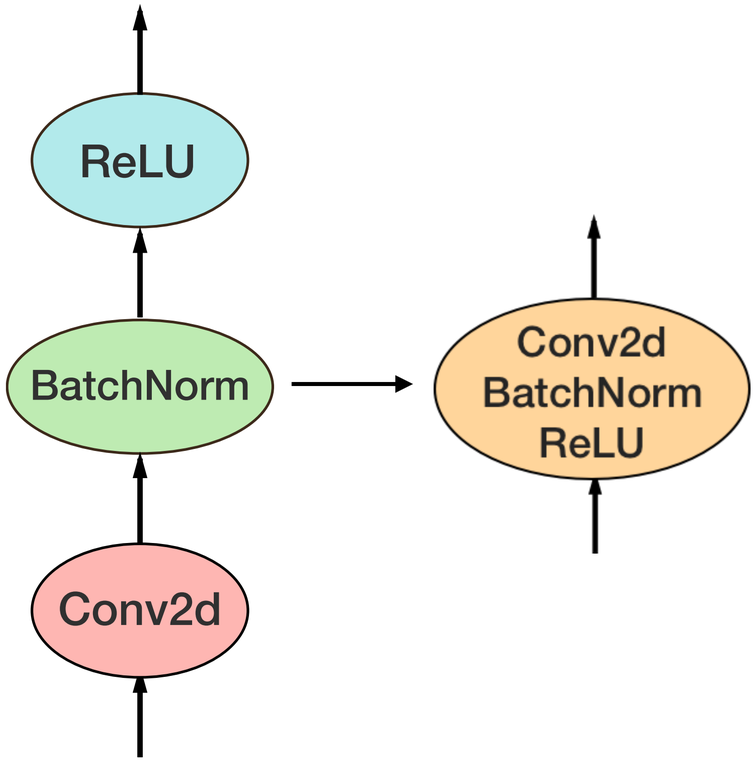
- 200+ operations, similar to numpy
- very fast acceleration on NVIDIA GPUs

Upcoming feature:
Distributed PyTorch

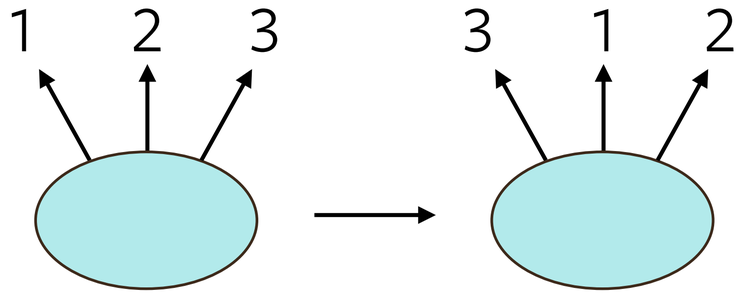
Planned Feature:
JIT Compilation

Compilation benefits

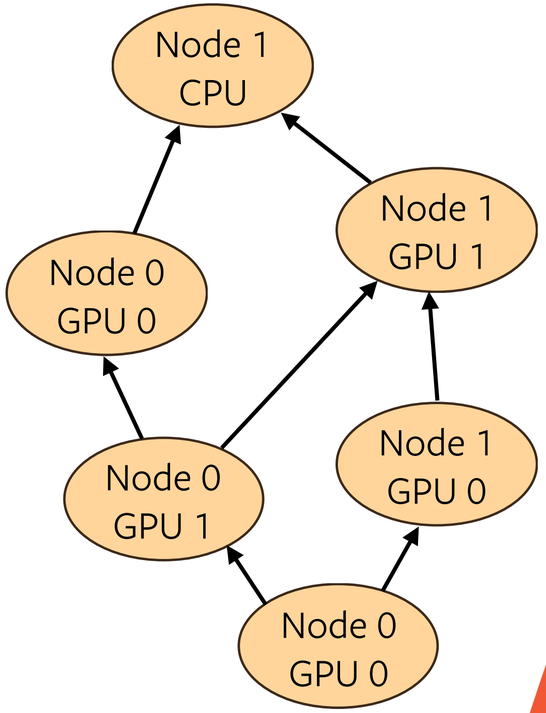
Kernel fusion



Out-of-order execution



Automatic work placement



JIT Compilation

- Possible in define-by-run Frameworks
- The key idea is deferred or lazy evaluation
  - y = x + 2
  - z = y * y
  - # nothing is executed yet, but the graph is being constructed
  - print(z) # now the entire graph is executed: z = (x+2) * (x+2)
- We can do just in time compilation on the graph before execution

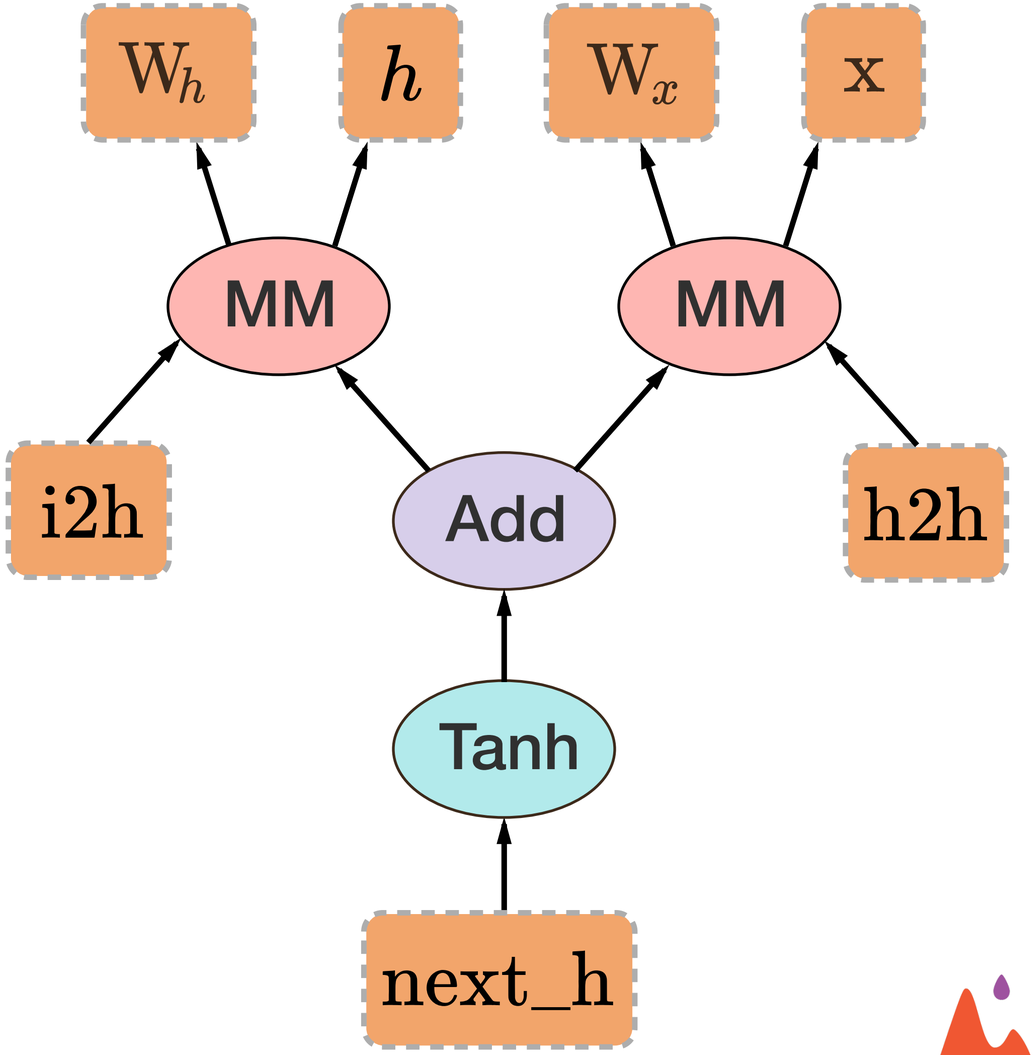
Lazy Evaluation

```
from torch.autograd import Variable

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

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))
```



Lazy Evaluation

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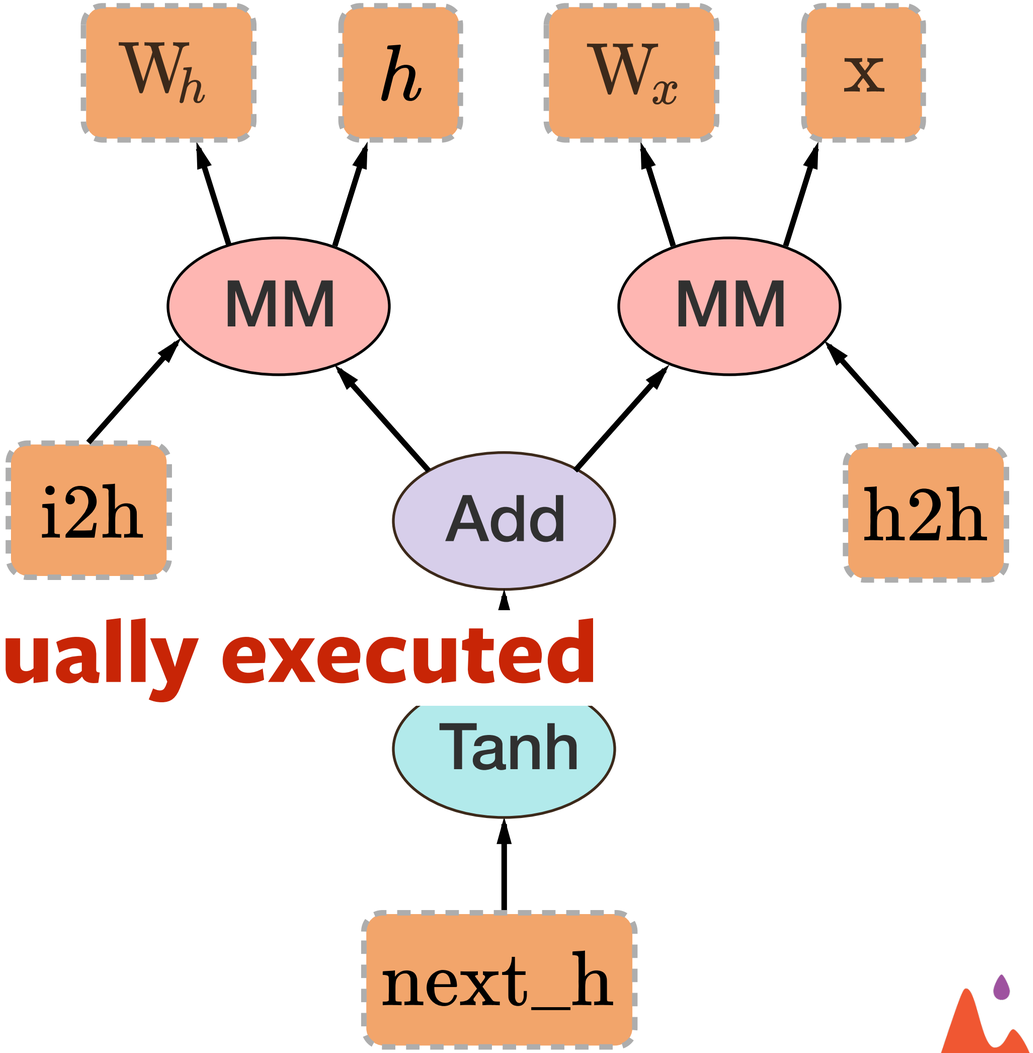
W_x = Variable(torch.randn(20, 10))

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

Graph built but not actually executed



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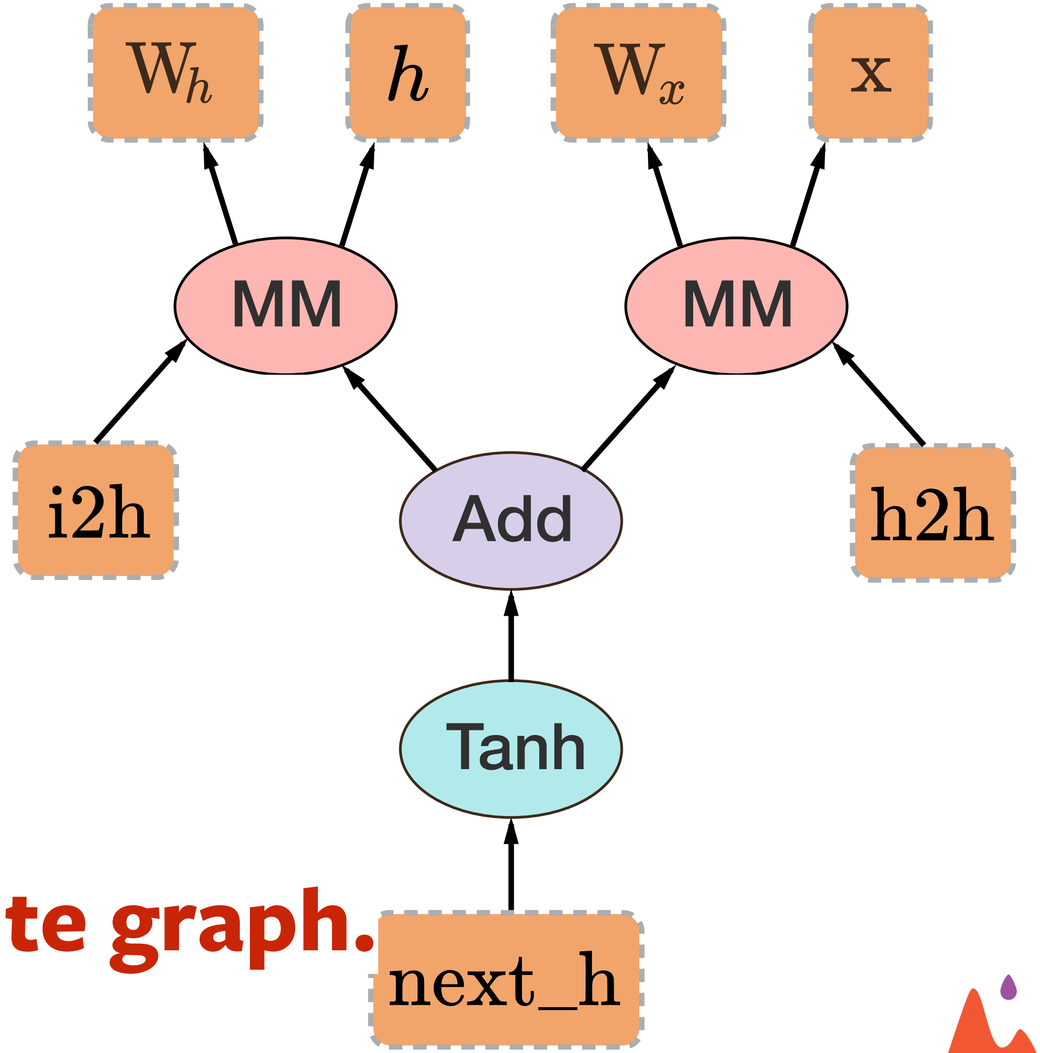
prev_h = Variable(torch.randn(1, 20))
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))

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

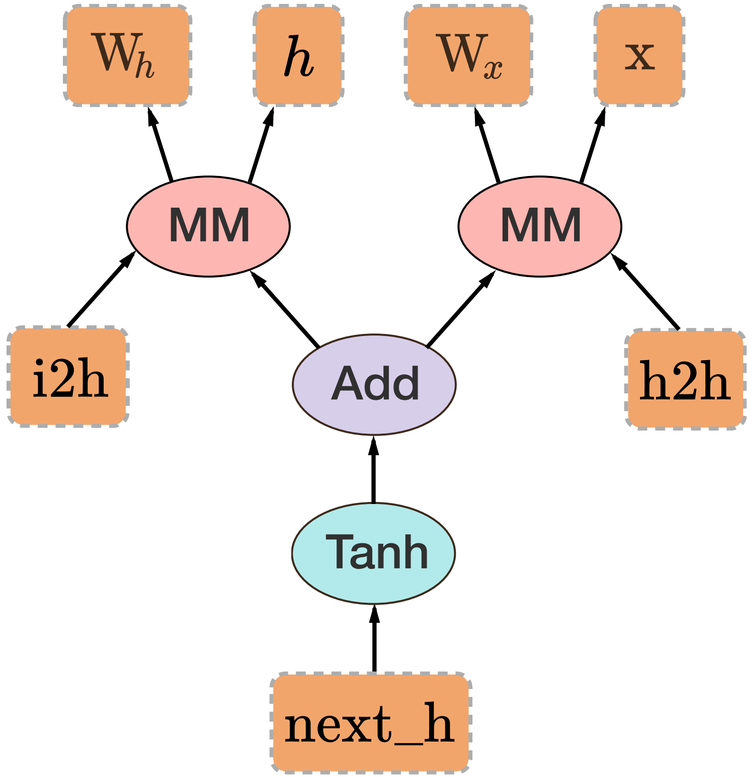
print(next_h)
```

Data accessed. Execute graph.



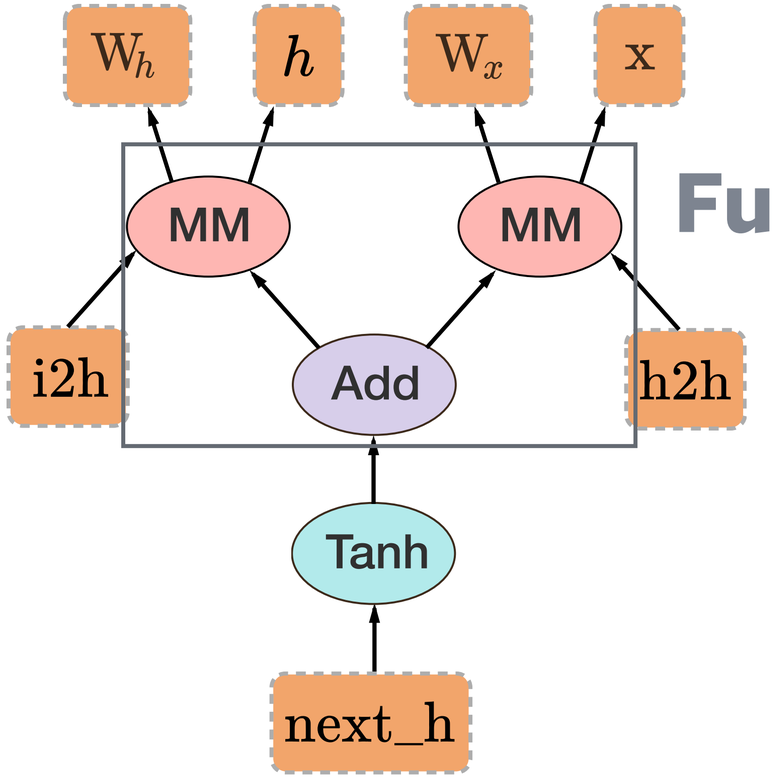
Lazy Evaluation

- A little bit of time between building and executing graph
  - Use it to compile the graph just-in-time



JIT Compilation

- Fuse and optimize operations



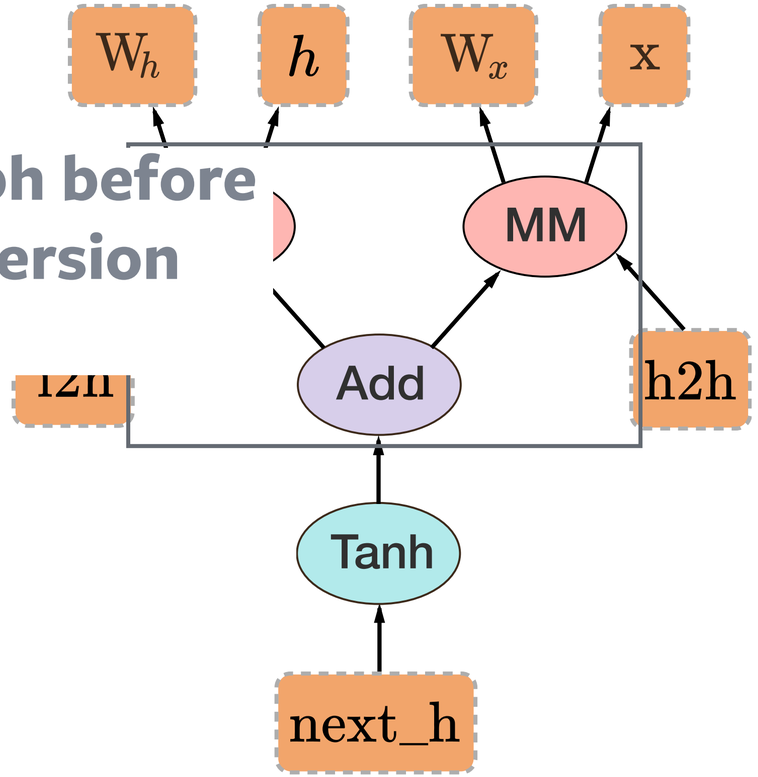
Fuse operations. Ex:

```
1   x = [0, 1, 2, 3, 4]
2   for i in range(len(x)):
3     x[i] = x[i] + 1
4
5   for i in range(len(x)):
6     x[i] = x[i] * 2
7
8
9   # Fused
10  for i in range(len(x)):
11    x[i] = (x[i] + 1) * 2
```

JIT Compilation

- Cache subgraphs

I've seen this part of the graph before let me pull up the compiled version from cache



JIT Compilation

- Possible in Dynamic Frameworks
- The key idea is deferred or lazy evaluation
  - y = x + 2
  - z = y * y
  - # nothing is executed yet, but the graph is being constructed
  - print(z) # now the entire graph is executed: z = (x+2) * (x+2)
- We can do just in time compilation on the graph before execution
- We can cache repeating patterns in subsets of the graph
  - to avoid recompilation
- Compiler is very different from Ahead-of-time compiler
  - fast compilation
  - compile traces rather than full graph

Summary

- Fast ndarray library with GPU support
- Build the latest neural networks and do gradient based learning using the autograd and neural network package
- large community of people, many companies using and contributing

PYTORCH

http://pytorch.org

Released Jan 18th

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You?


PYTORCH