DeepRob

Lecture 11
Deep Learning Software
University of Michigan and University of Minnesota

Project 2—Updates

- Instructions available on the website
  - Here: https://rpm-lab.github.io/CSCI5980-Spr23-DeepRob/projects/project2/
- Implement two-layer neural network and generalize to FCN
- **Autograder is online!**
- **Due Today Tuesday, February 21st 11:59 PM CT**

Project 3 — Will be out tonight

- **Due Tuesday, March 14th 11:59 PM CT**

Final Project Tasks

1. [Graded] Final Project Proposal document submission (2%)
2. [Graded] In-class topic-paper(s) presentation (4%)
3. In-class final project pitch
4. In-class final project checkpoint
5. [Graded] Reproduce published results (12%)
   - Algorithmic extension to obtain results with new idea, technique or dataset
6. [Graded] Video Presentation + Poster (4%)
7. [Graded] Final Report (2%)

Final Project Tasks

1. [Graded] Final Project Proposal document submission (2%)
2. [Graded] In-class topic-paper(s) presentation (4%)
3. In-class final project p
4. In-class final project c
5. [Graded] Reproduce
   - Algorithmic extens … que or dataset
6. [Graded] Video Prese
7. [Graded] Final Repor

Recommendations:
1. Each member will read a paper in the topic.
2. Meet with the team and discuss your notes on the papers.
3. Select a paper your team want to reproduce-extend…

Paper selection due on 02/24.

A google form will be sent out soon…

Final Project Proposal due 03/02

A template will be sent out soon…

Final Project Tasks

1. [Graded] Final Project Proposal document submission (2%)
2. [Graded] In-class topic-paper(s) presentation (4%)
3. In-class final project pitch
4. In-class final project c...ckpoint
5. [Graded] Reproduce ...
   - Algorithmic extens... ...nique or dataset
6. [Graded] Video Prese...
7. [Graded] Final Report ...

Student lecture-presentations starting 03/02

If you presenting on a Tuesday

Meet with me during OH the previous Wednesday

If you presenting on a Thursday

Meet with me during OH the previous Friday

Recap: Training Neural Networks

1. **One time setup:**
   - Activation functions, data preprocessing, weight initialization, regularization
2. **Training dynamics:**
   - Learning rate schedules; hyperparameter optimization
3. **After training:**
   - Model ensembles, transfer learning

A zoo of frameworks!

Caffe
(UC Berkeley) → Caffe2
(Facebook)

Torch
(NYU / Facebook) → PyTorch
(Facebook)

Theano
(U Montreal) → TensorFlow
(Google)

Darknet
(Redmon)

Chainer

MXNet
(Amazon)
Developed by U Washington, CMU, MIT, Hong Kong U, etc. but main framework of choice at AWS

CNTK
(Microsoft)

PaddlePaddle
(Baidu)

JAX
(Google)

A zoo of frameworks!

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We'll focus on these

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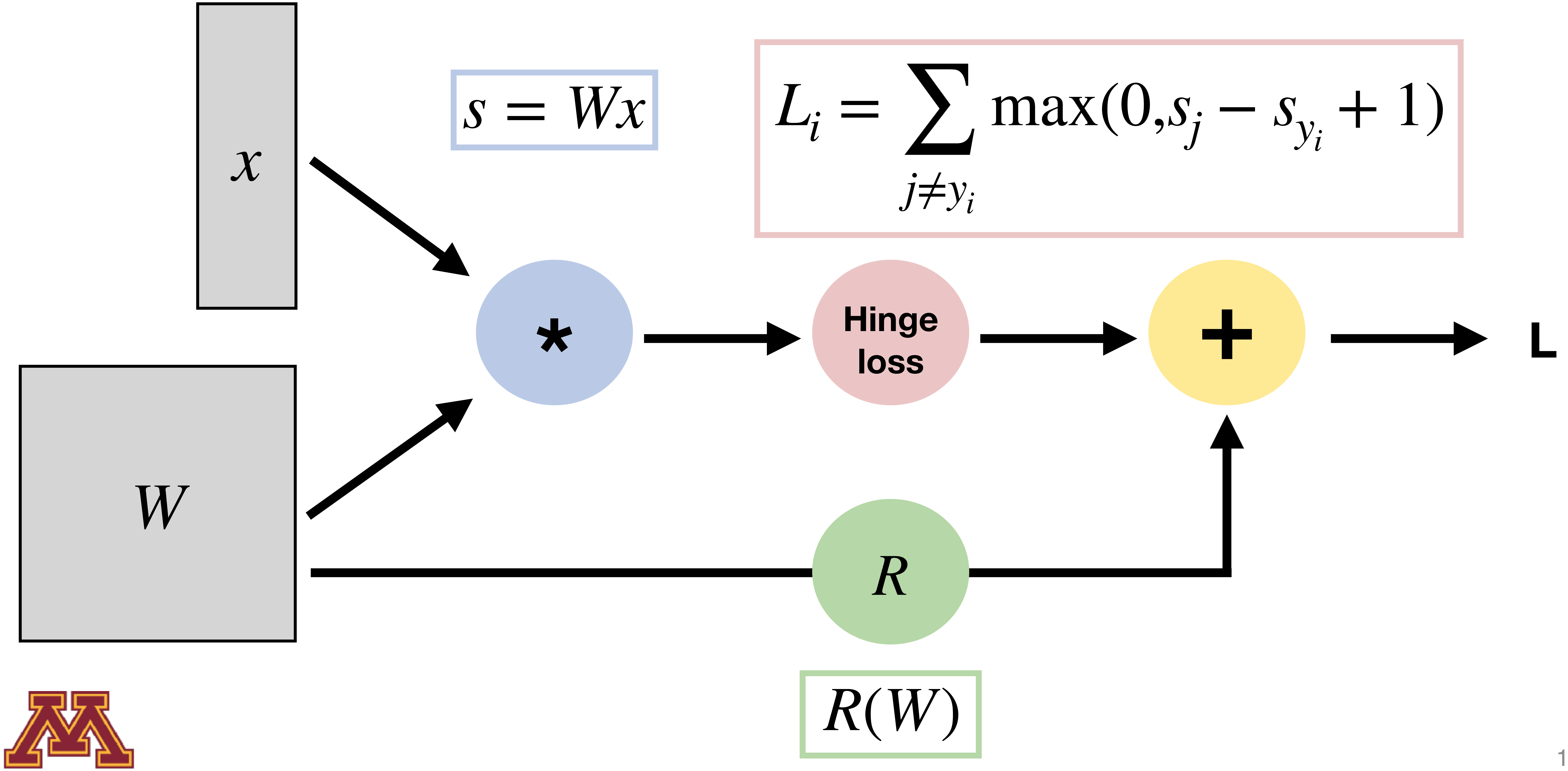
Recall: Computational Graphs



The motivation for deep learning frameworks

1. Allow rapid prototyping of new ideas
2. Automatically compute gradients for you
3. Run it all efficiently on GPU or TPU hardware

PyTorch

PyTorch: Versions

For this class we are using **PyTorch version 1.13** (Released October 2022)

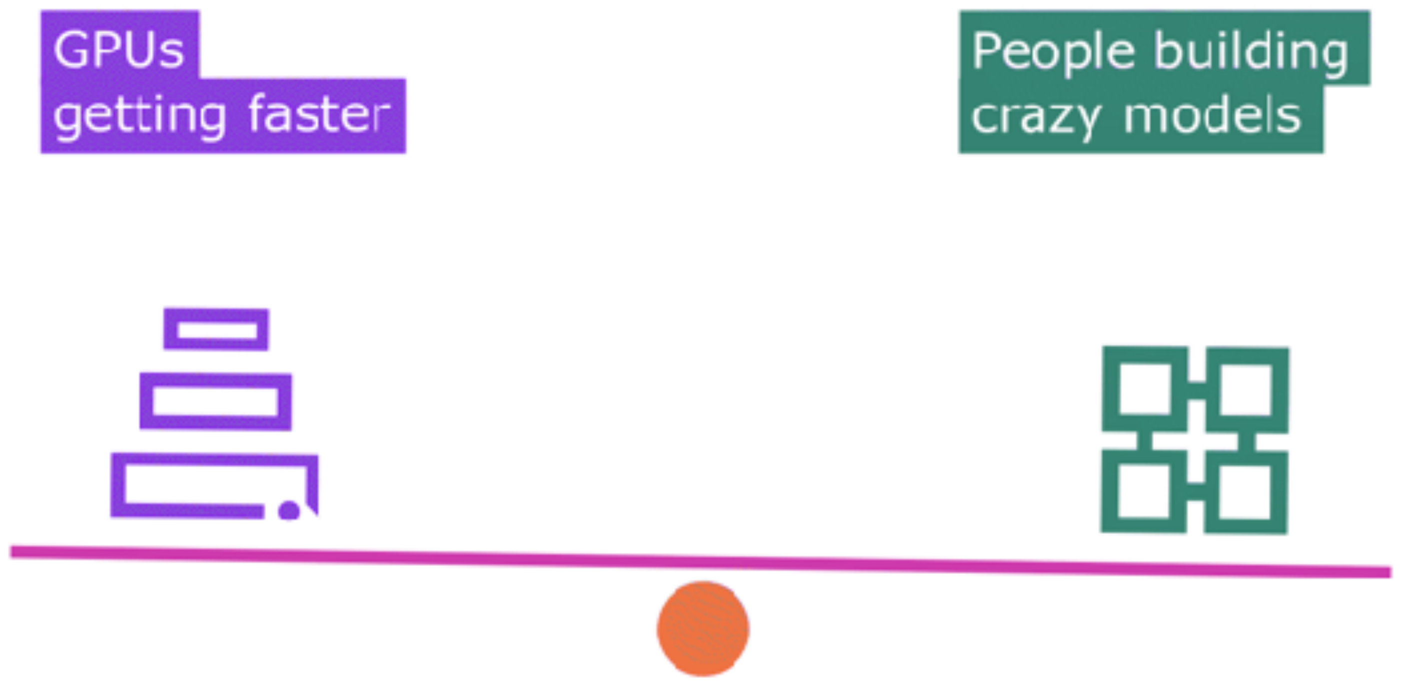
Be careful if you are looking at older PyTorch code—the API changed a lot before 1.0

PyTorch: Version 2.0

Introduced to further optimize models (`torch.compile`)

Intended to be backwards compatible with 1.x

Expected stable release in March 2023



Video credit: [PyTorch]

PyTorch: Fundamental Concepts

Tensor: Like a numpy array, but can run on GPU

Autograd: Package for building computational graphs out of Tensors, and automatically computing gradients

Module: A neural network layer; may store state or learnable weights

PyTorch: Fundamental Concepts

Tensor: Like a numpy array, but can run on GPU — **P0, P1, P2**

Autograd: Package for building computational graphs out of Tensors, and automatically computing gradients

Module: A neural network layer; may store state or learnable weights

P3
P4
Final

PyTorch: Tensors

Running example:

Train a two-layer ReLU network on random data with L2 loss

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Create random tensors for data and weights

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Forward pass: compute predictions and loss

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Backward pass: manually compute gradients

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

Gradient descent step on weights

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Tensors

To run on GPU, just use a different device!

```
import torch

device = torch.device('cpu')

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in, device=device)
y = torch.randn(N, D_out, device=device)
w1 = torch.randn(D_in, H, device=device)
w2 = torch.randn(H, D_out, device=device)

learning_rate = 1e-6
for t in range(500):
    h = x.mm(w1)
    h_relu = h.clamp(min=0)
    y_pred = h_relu.mm(w2)
    loss = (y_pred - y).pow(2).sum()

    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)

    w1 -= learning_rate * grad_w1
    w2 -= learning_rate * grad_w2
```

PyTorch: Autograd

Creating Tensors with requires_grad=True enables autograd

Operations on Tensors with requires_grad=True cause PyTorch to build a computational graph

```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

We will not want gradients (of loss) with respect to data

Do want gradients with respect to weights

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

Compute gradients with respect to all inputs that have requires_grad=True!

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

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    with torch.no_grad():
        w1 -= learning_rate * w1.grad
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        w2.grad.zero_()
```
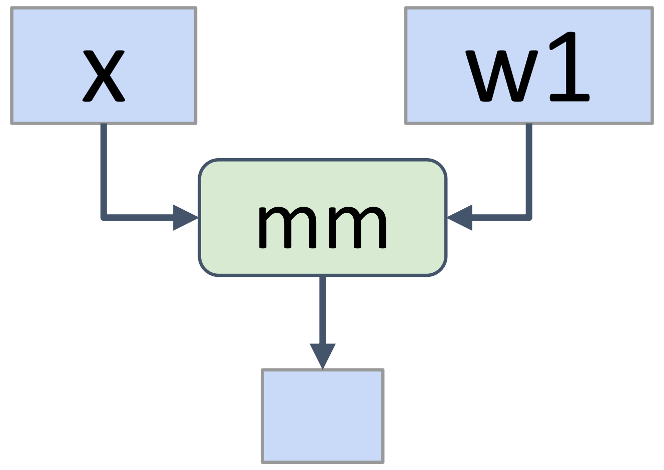

PyTorch: Autograd



Every operation on a tensor with requires_grad=True will add to the computational graph, and the resulting tensors will also have requires_grad=True

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

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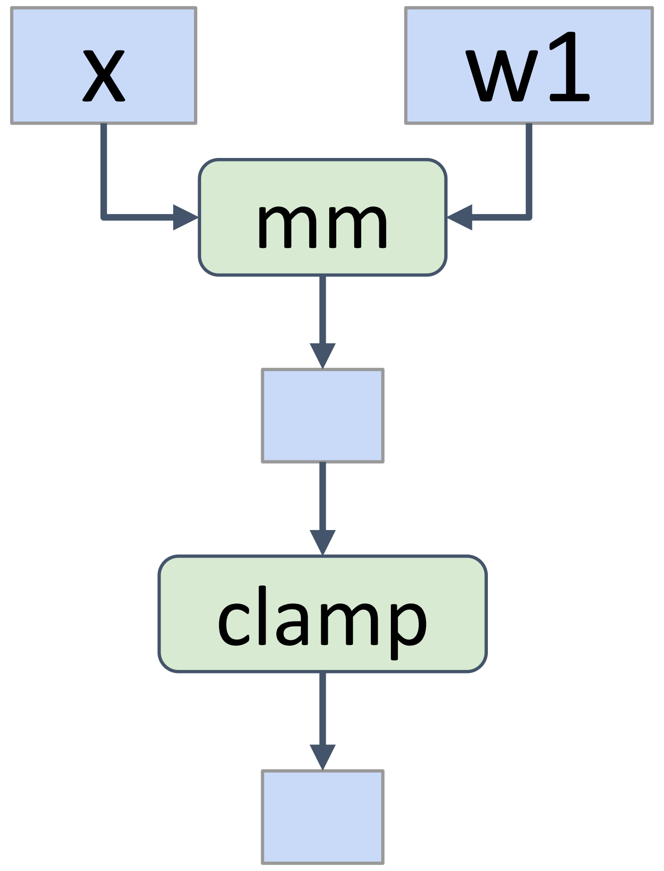
PyTorch: Autograd



Every operation on a tensor with requires_grad=True will add to the computational graph, and the resulting tensors will also have requires_grad=True

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
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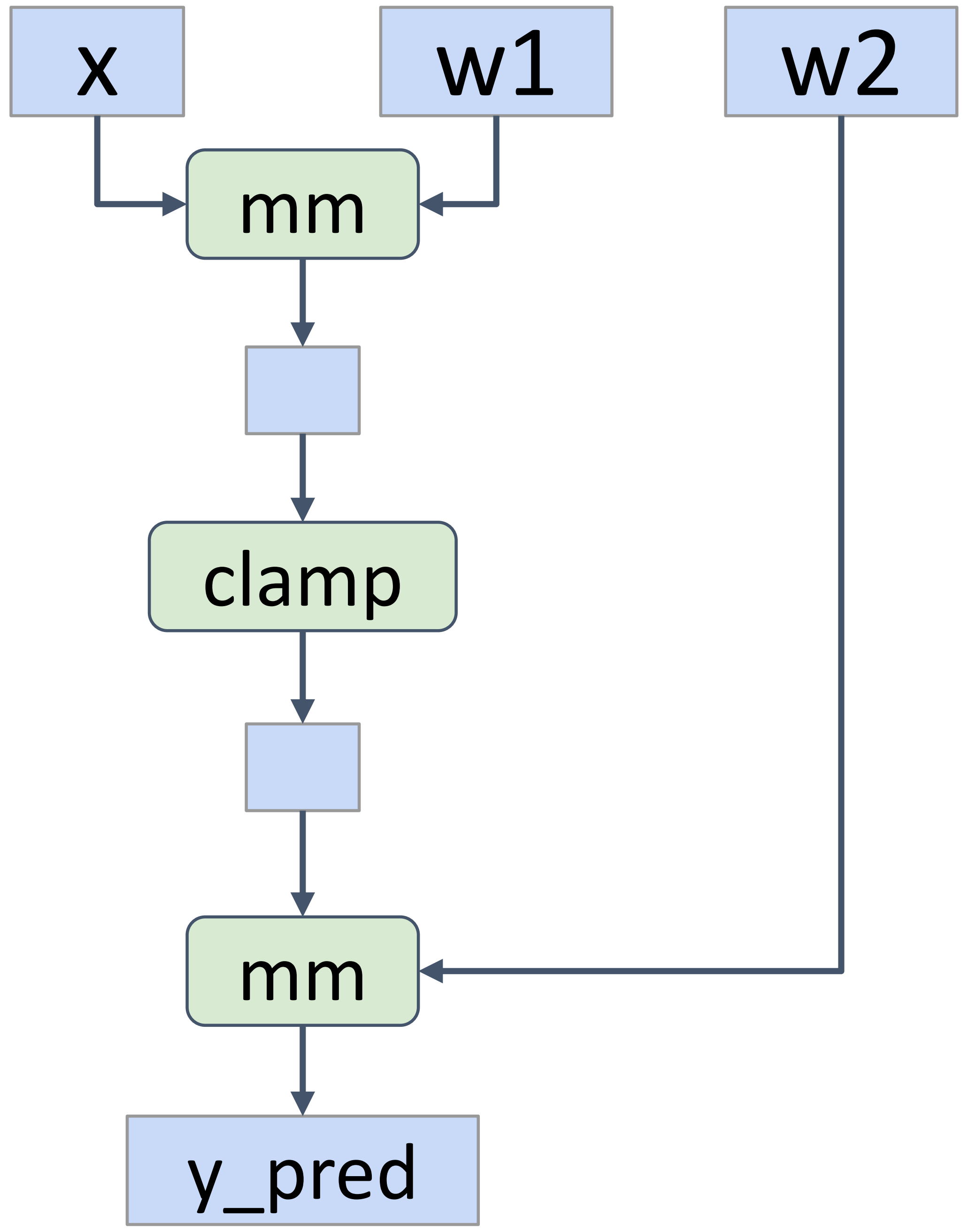
```

PyTorch: Autograd




```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
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    loss.backward()

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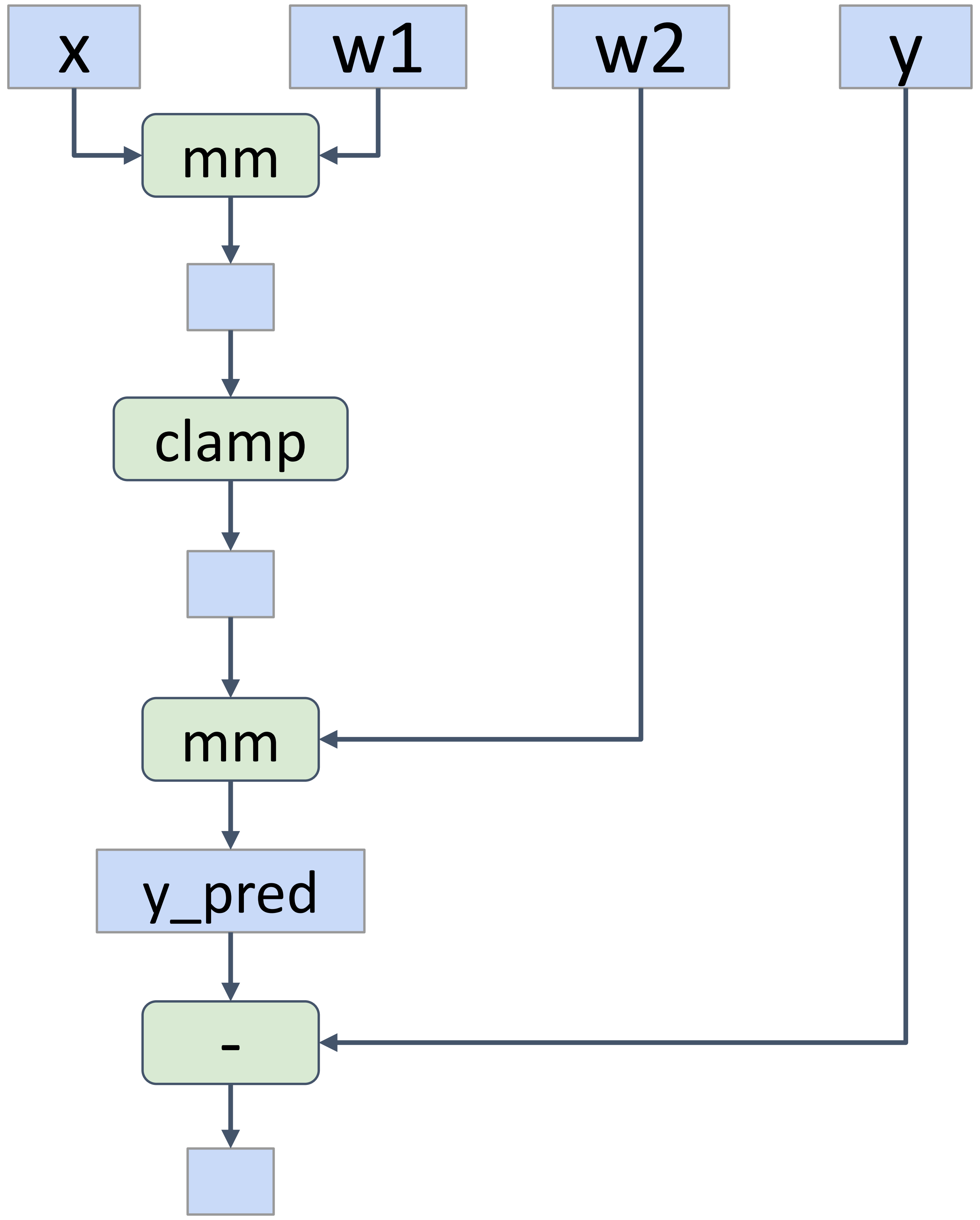
```

PyTorch: Autograd




```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
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w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
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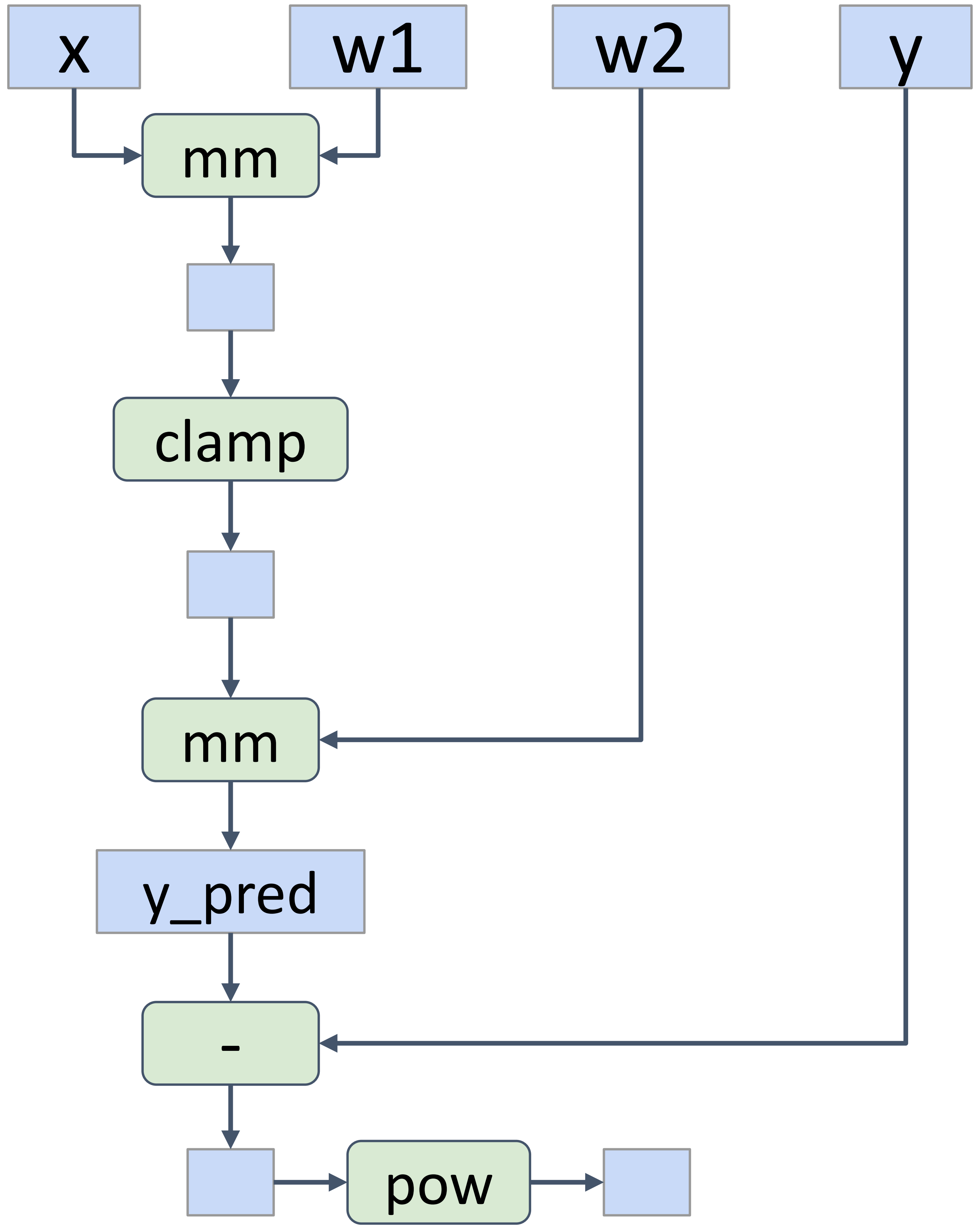
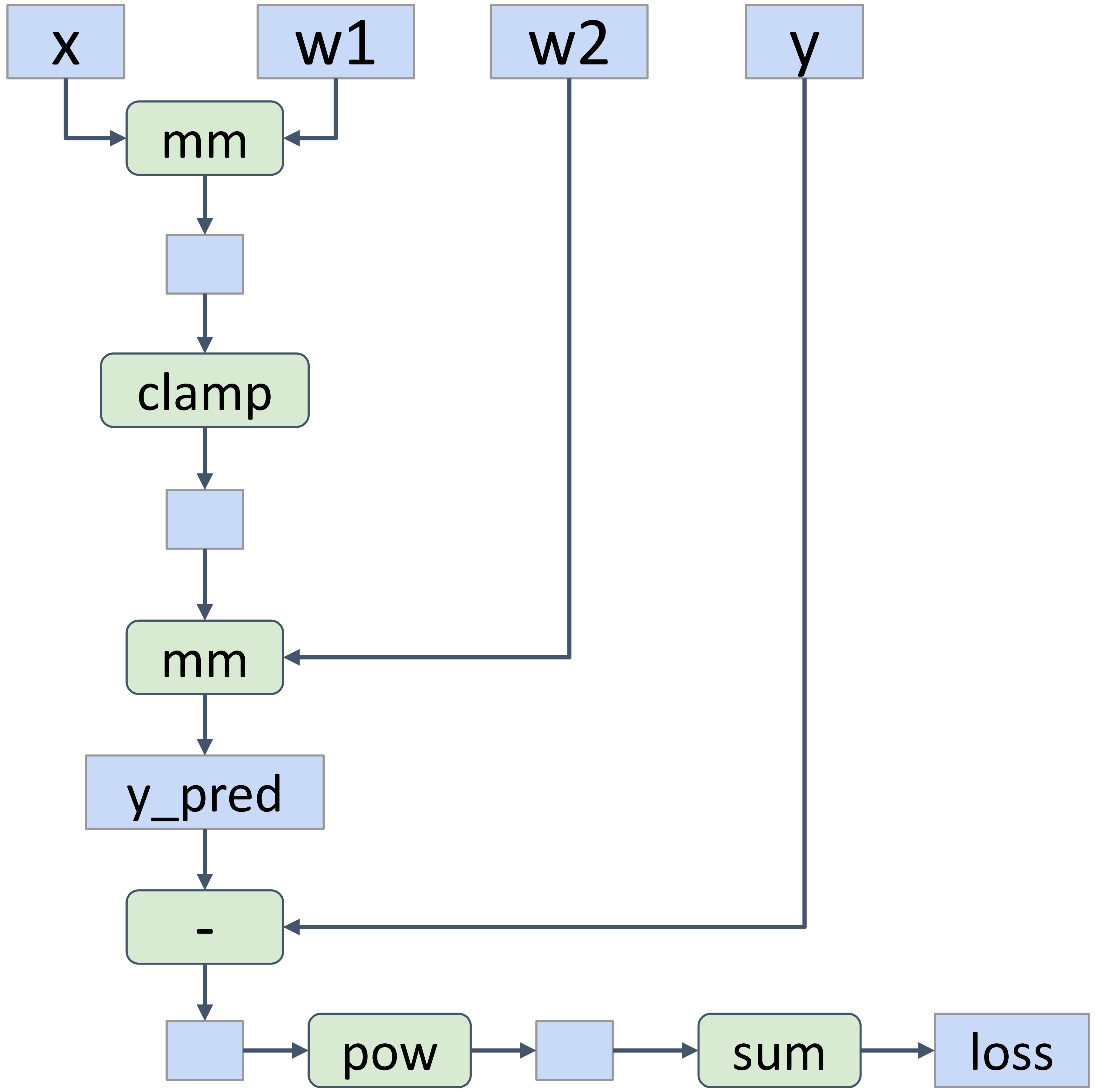
PyTorch: Autograd



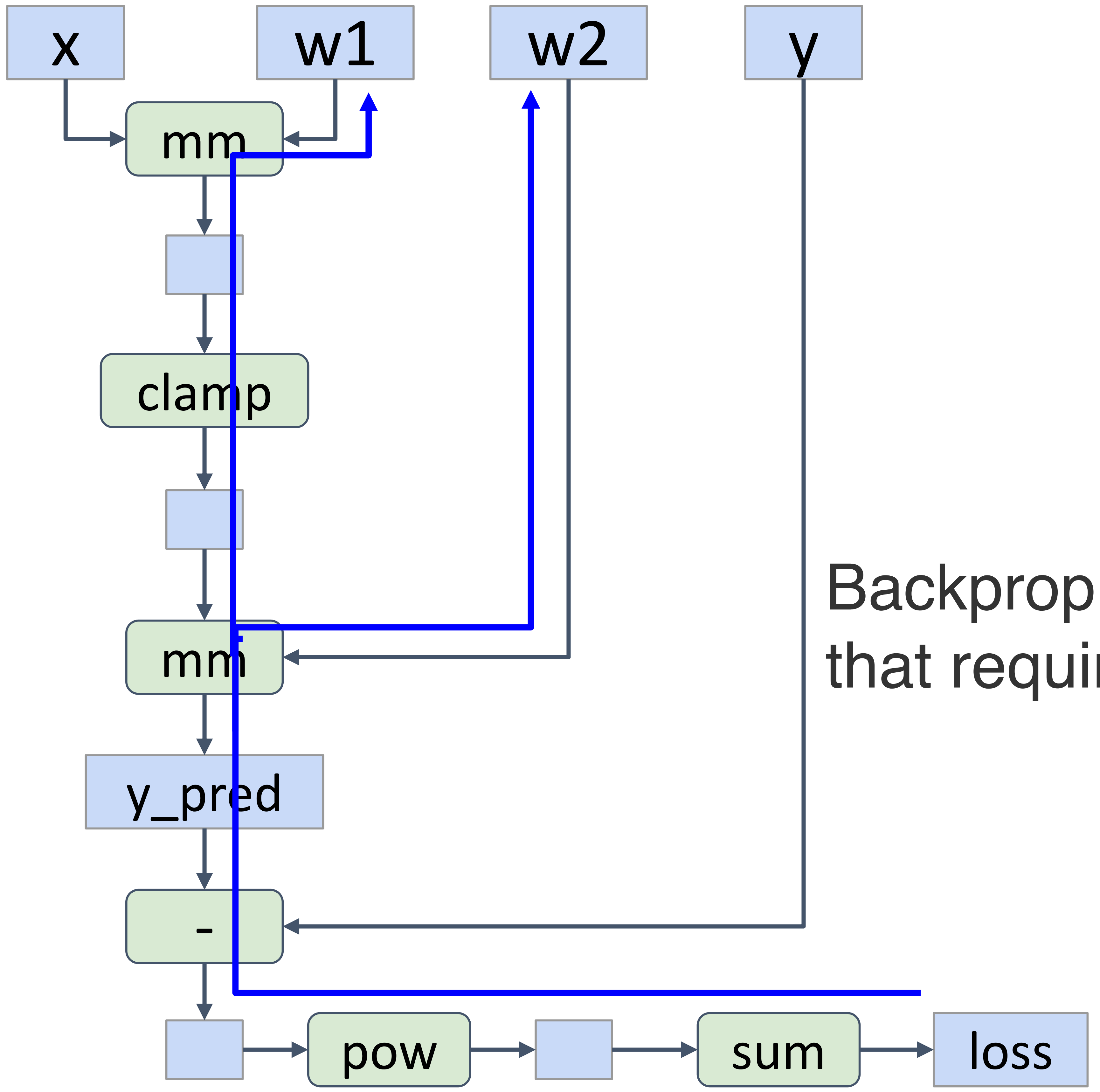

```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd




```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd



Backprop to all inputs that require grad

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

x w1 w2 y

After backward finishes, gradients are accumulated into w1.grad and w2.grad and the graph is destroyed

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

x w1 w2 y

After backward finishes, gradients are accumulated into w1.grad and w2.grad and the graph is destroyed

Make gradient step on weights

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

x w1 w2 y

After backward finishes, gradients are accumulated into w1.grad and w2.grad and the graph is destroyed

Set gradients to zero—forgetting this is a common bug!

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: Autograd

x w1 w2 y

After backward finishes, gradients are accumulated into w1.grad and w2.grad and the graph is destroyed

Tell PyTorch not to build a graph for these operations

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()

    with torch.no_grad():
        w1 -= learning_rate * w1.grad
        w2 -= learning_rate * w2.grad
        w1.grad.zero_()
        w2.grad.zero_()
```

PyTorch: New Functions

Can define new operations using Python functions

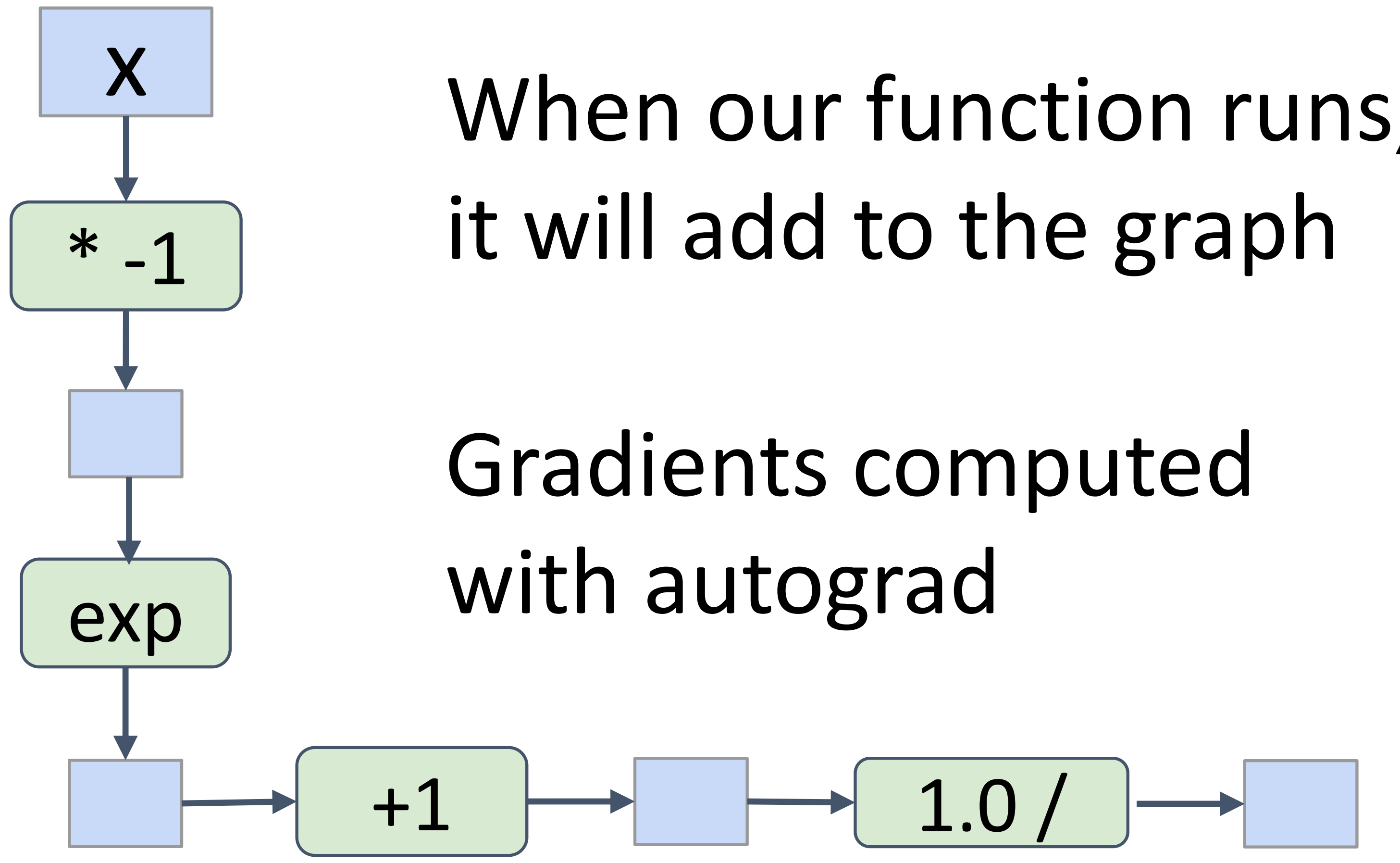
```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
  y_pred = sigmoid(x.mm(w1)).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  if t % 50 == 0:
    print(t, loss.item())

  with torch.no_grad():
    w1 -= learning_rate * w1.grad
    w2 -= learning_rate * w2.grad
    w1.grad.zero_()
    w2.grad.zero_()
```

PyTorch: New Functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



When our function runs, it will add to the graph

Gradients computed with autograd

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10

x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
  y_pred = sigmoid(x.mm(w1)).mm(w2)
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  loss.backward()
  if t % 50 == 0:
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  with torch.no_grad():
    w1 -= learning_rate * w1.grad
    w2 -= learning_rate * w2.grad
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    w2.grad.zero_()
```
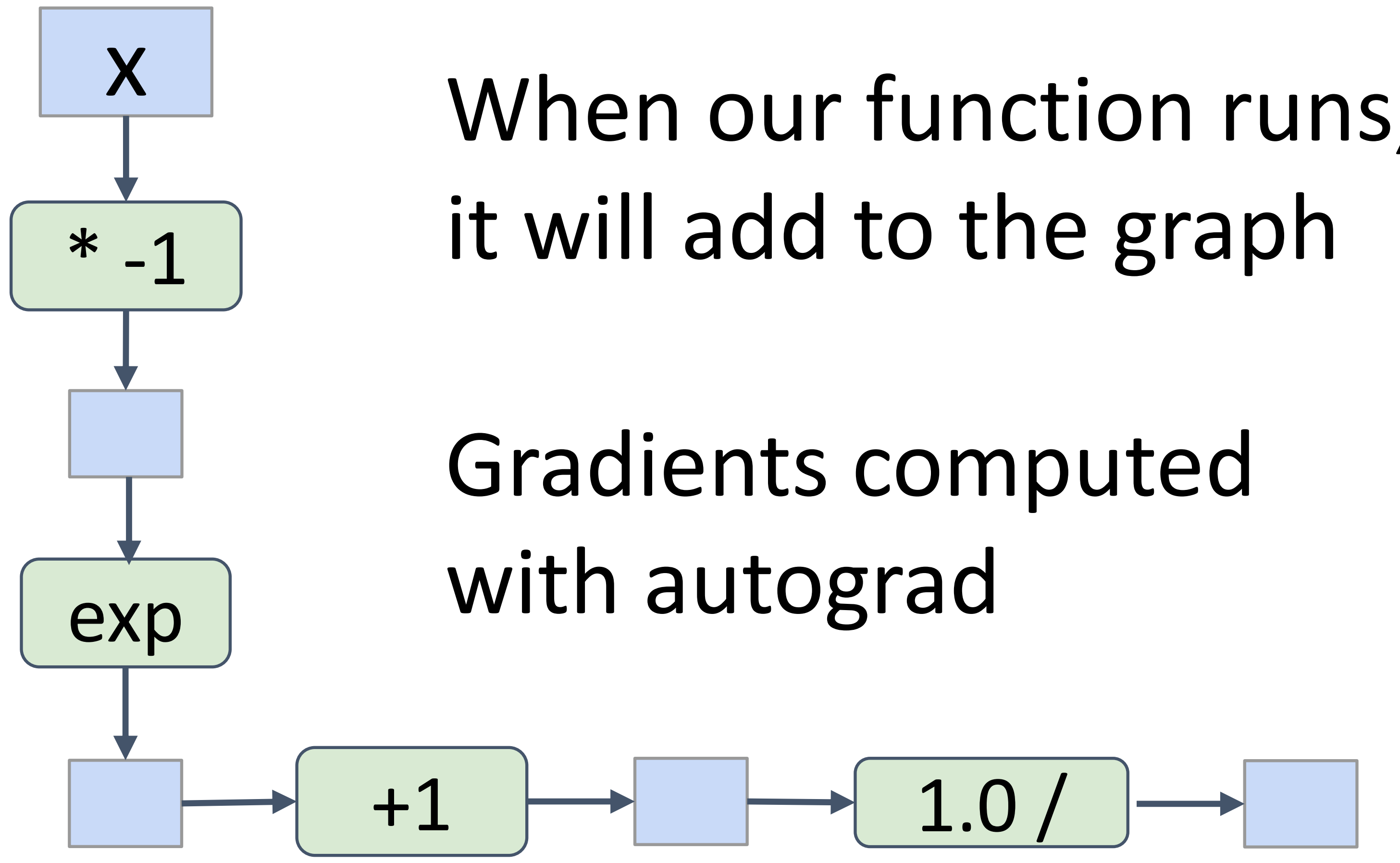

PyTorch: New Functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

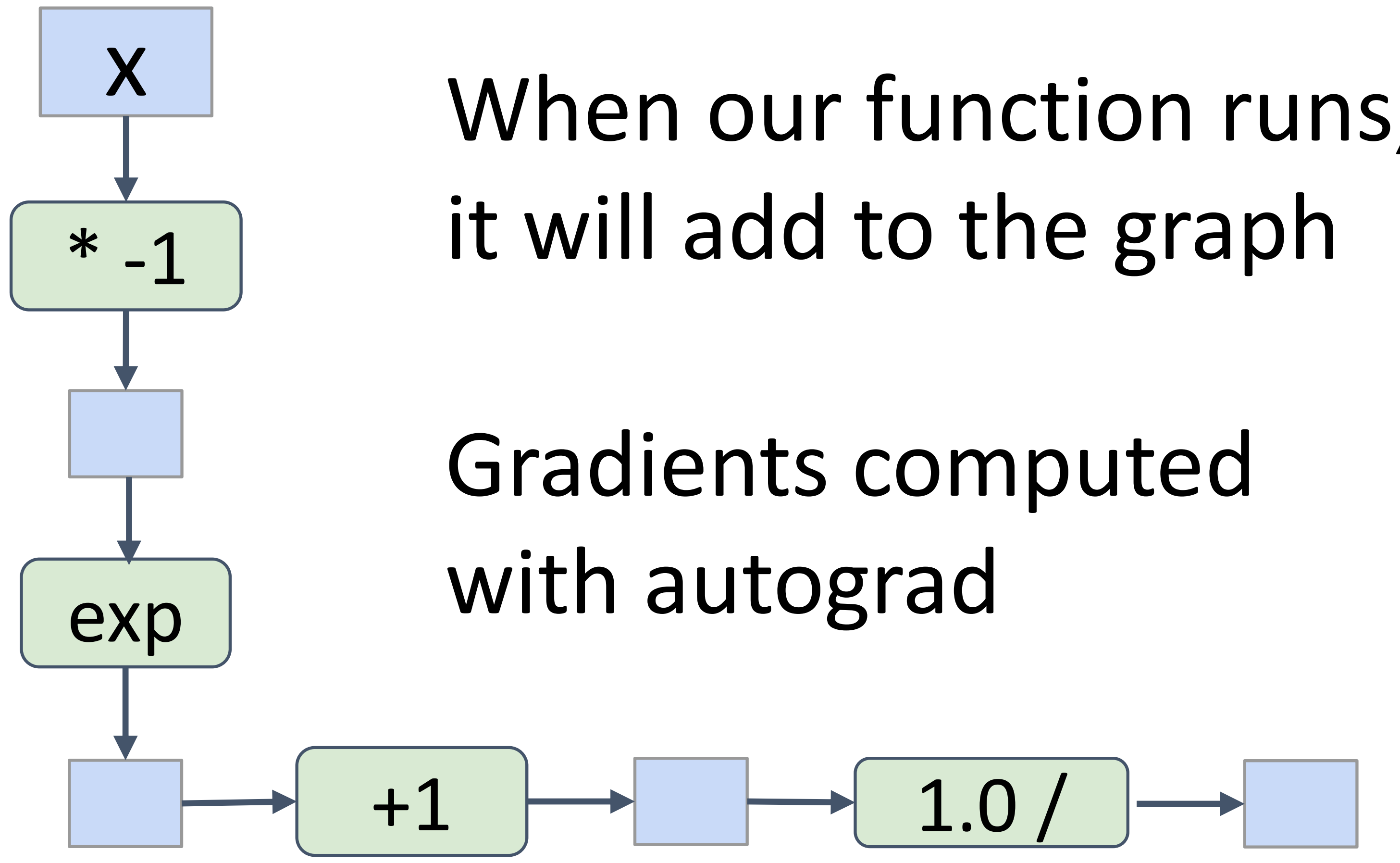
```
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

Recall: $$\frac{\partial}{\partial x}\left[\sigma(x)\right] = (1 - \sigma(x))\sigma(x)$$

PyTorch: New Functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



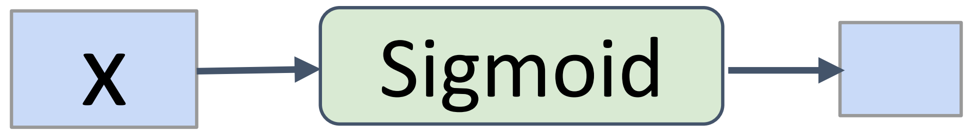
When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

```
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

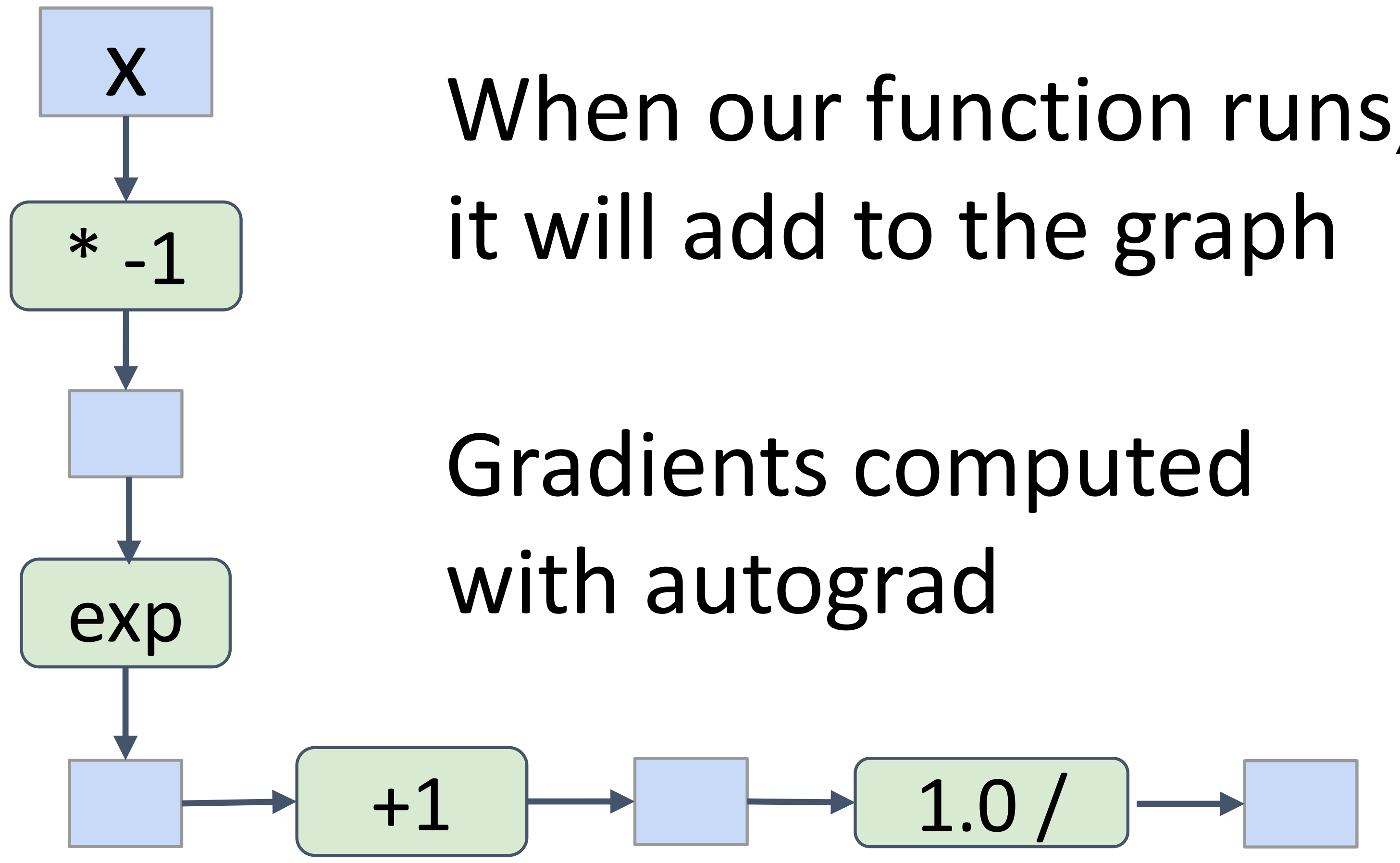
Now when our function runs, it adds one node to the graph!



PyTorch: New Functions

Can define new operations using Python functions

```
def sigmoid(x):
  return 1.0 / (1.0 + (-x).exp())
```



When our function runs, it will add to the graph

Gradients computed with autograd

Define new autograd operators by subclassing Function, define forward and backward

```
class Sigmoid(torch.autograd.Function):
  @staticmethod
  def forward(ctx, x):
    y = 1.0 / (1.0 + (-x).exp())
    ctx.save_for_backward(y)
    return y

  @staticmethod
  def backward(ctx, grad_y):
    y, = ctx.saved_tensors
    grad_x = grad_y * y * (1.0 - y)
    return grad_x

def sigmoid(x):
  return Sigmoid.apply(x)
```

In practice this is pretty rare – in most cases Python functions are good enough

PyTorch: nn

Higher-level wrapper for working with neural nets

Use this! It will make your life easier

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Object-oriented API: Define model object as sequence of layers objects, each of which holds weight tensors

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Forward pass: Feed data to model and compute loss

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Forward pass: Feed data to model and compute loss

torch.nn.functional has useful helpers like loss functions

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Backward pass: compute gradient with respect to all model weights (they have requires_grad=True)

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: nn

Make gradient step on each model parameter (with gradients disabled)

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-2
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    with torch.no_grad():
        for param in model.parameters():
            param -= learning_rate * param.grad
    model.zero_grad()
```

PyTorch: optim

Use an **optimizer** for different update rules

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: optim

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
          torch.nn.Linear(D_in, H),
          torch.nn.ReLU(),
          torch.nn.Linear(H, D_out))

learning_rate = 1e-4
optimizer = torch.optim.Adam(model.parameters(),
                             lr=learning_rate)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()

    optimizer.step()
    optimizer.zero_grad()
```

After computing gradients, use optimizer to update and zero gradients

PyTorch: nn
Defining Modules

A PyTorch **Module** is a neural net layer; it inputs and outputs Tensors

Modules can contain weights or other modules

Very common to define your own models or layers as custom Modules

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn
Defining Modules

Define our whole model as a single Module

```python
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn
Defining Modules

Initializer sets up two children (Modules can contain modules)

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn
Defining Modules

Define forward pass using child modules and tensor operations

No need to define backward - autograd will handle it

```
import torch

class TwoLayerNet(torch.nn.Module):
    def __init__(self, D_in, H, D_out):
        super(TwoLayerNet, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, H)
        self.linear2 = torch.nn.Linear(H, D_out)

    def forward(self, x):
        h_relu = self.linear1(x).clamp(min=0)
        y_pred = self.linear2(h_relu)
        return y_pred

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)

    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

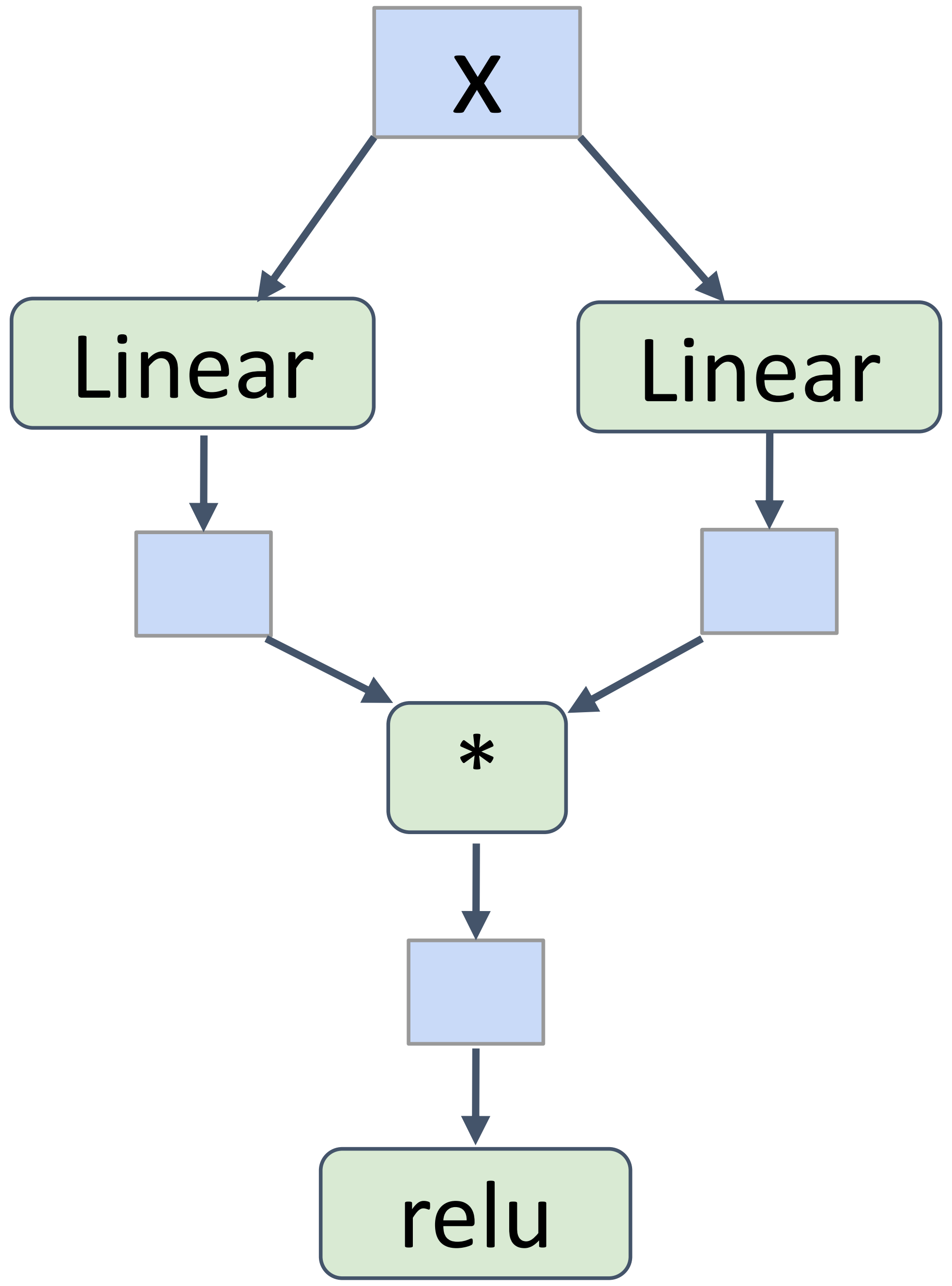
PyTorch: nn
Defining Modules

Very common to mix and match custom Module subclasses and Sequential containers

```
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
            ParallelBlock(D_in, H),
            ParallelBlock(H, H),
            torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn
Defining Modules

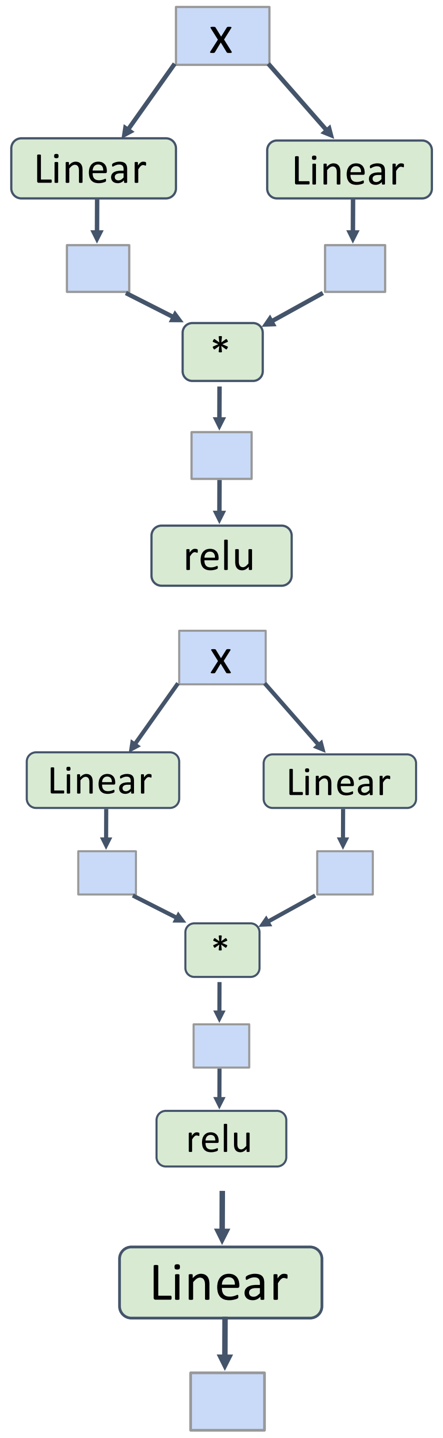
Define network component as a Module subclass




```python
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
            ParallelBlock(D_in, H),
            ParallelBlock(H, H),
            torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: nn
Defining Modules

Stack multiple instances of the component in a sequential



Very easy to quickly build complex network architectures!

```python
import torch

class ParallelBlock(torch.nn.Module):
    def __init__(self, D_in, D_out):
        super(ParallelBlock, self).__init__()
        self.linear1 = torch.nn.Linear(D_in, D_out)
        self.linear2 = torch.nn.Linear(D_in, D_out)
    def forward(self, x):
        h1 = self.linear1(x)
        h2 = self.linear2(x)
        return (h1 * h2).clamp(min=0)

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

model = torch.nn.Sequential(
            ParallelBlock(D_in, H),
            ParallelBlock(H, H),
            torch.nn.Linear(H, D_out))

optimizer = torch.optim.Adam(model.parameters(), lr=1e-4)
for t in range(500):
    y_pred = model(x)
    loss = torch.nn.functional.mse_loss(y_pred, y)
    loss.backward()
    optimizer.step()
    optimizer.zero_grad()
```

PyTorch: DataLoaders

A **DataLoader** wraps a **Dataset** and provides minibatching, shuffling, multithreading, for you

When you need to load custom data, just write your own Dataset class

```
import torch
from torch.utils.data import TensorDataset, DataLoader

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

loader = DataLoader(TensorDataset(x, y), batch_size=8)
model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-2)
for epoch in range(20):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred, y_batch)

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

PyTorch: DataLoaders

Iterate over loader to form minibatches

```
import torch
from torch.utils.data import TensorDataset, DataLoader

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)

loader = DataLoader(TensorDataset(x, y), batch_size=8)
model = TwoLayerNet(D_in, H, D_out)

optimizer = torch.optim.SGD(model.parameters(), lr=1e-2)
for epoch in range(20):
    for x_batch, y_batch in loader:
        y_pred = model(x_batch)
        loss = torch.nn.functional.mse_loss(y_pred, y_batch)

        loss.backward()
        optimizer.step()
        optimizer.zero_grad()
```

PyTorch: Pretrained Models

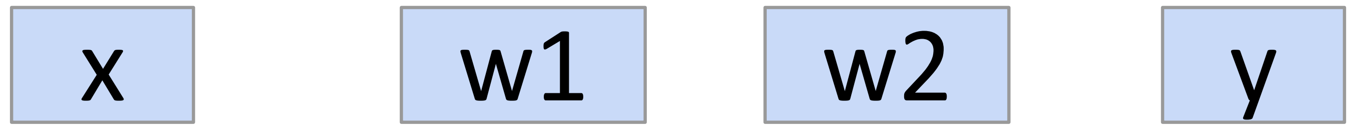
Super easy to use pertained models with torch vision
https://pytorch.org/vision/stable/

```
import torch
import torchvision

alexnet = torchvision.models.alexnet(pretrained=True)
vgg16 = torchvision.models.vgg16(pretrained=True)
resnet101 = torchvision.models.resnet101(pretrained=True)
```

PyTorch: Dynamic Computation Graphs

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

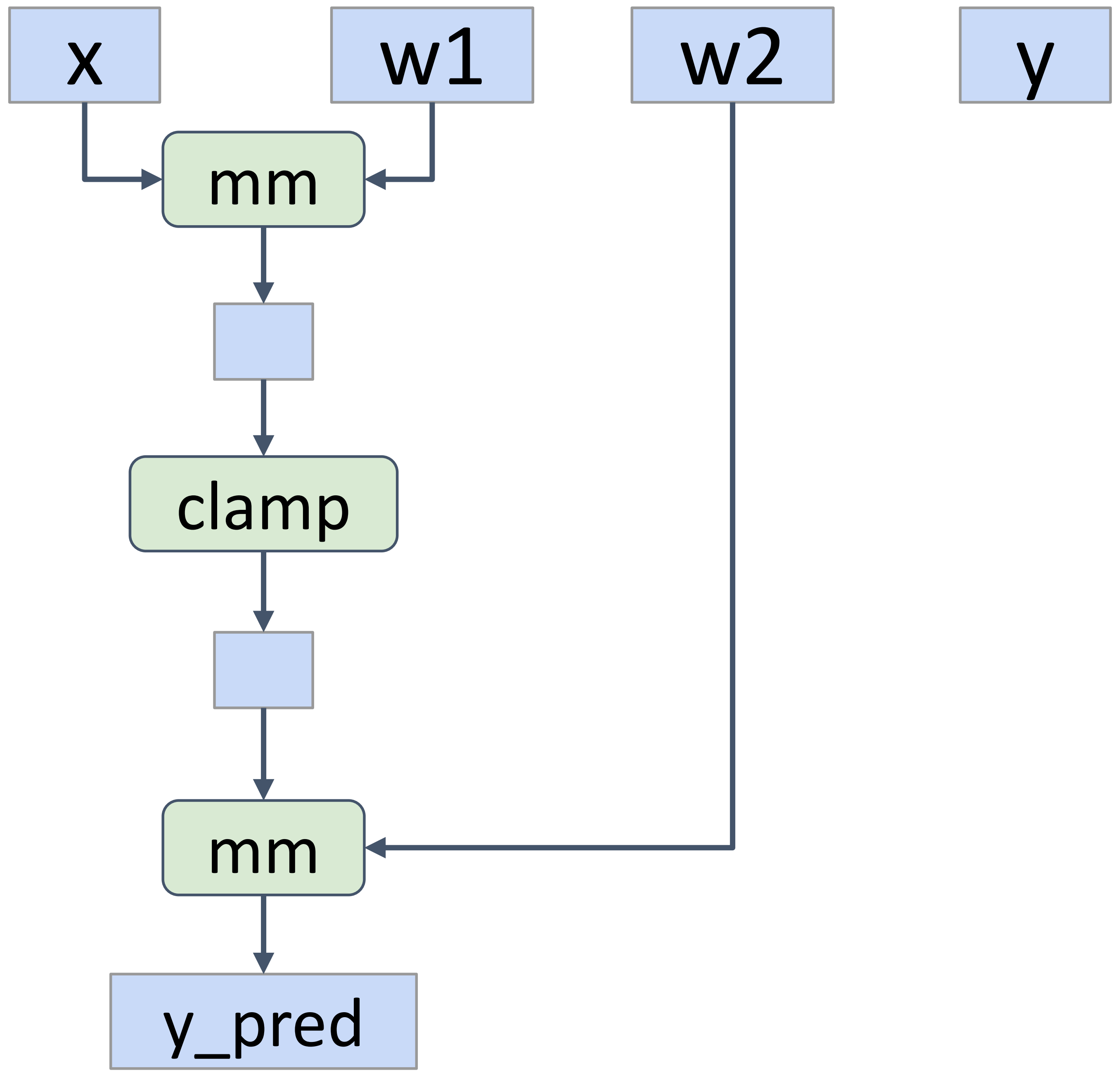
PyTorch: Dynamic Computation Graphs




```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Create Tensor objects

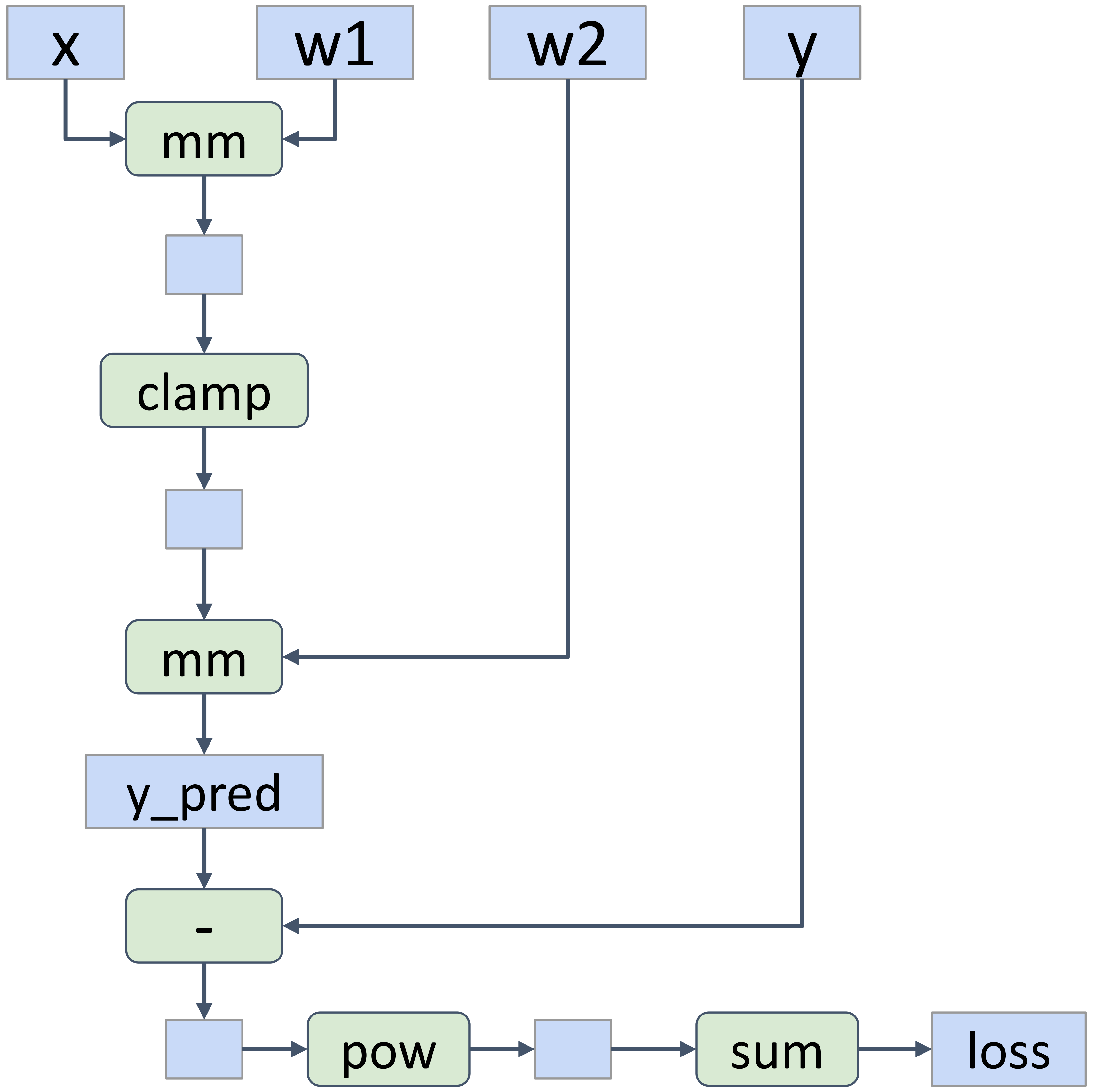
PyTorch: Dynamic Computation Graphs




```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure
AND perform computation

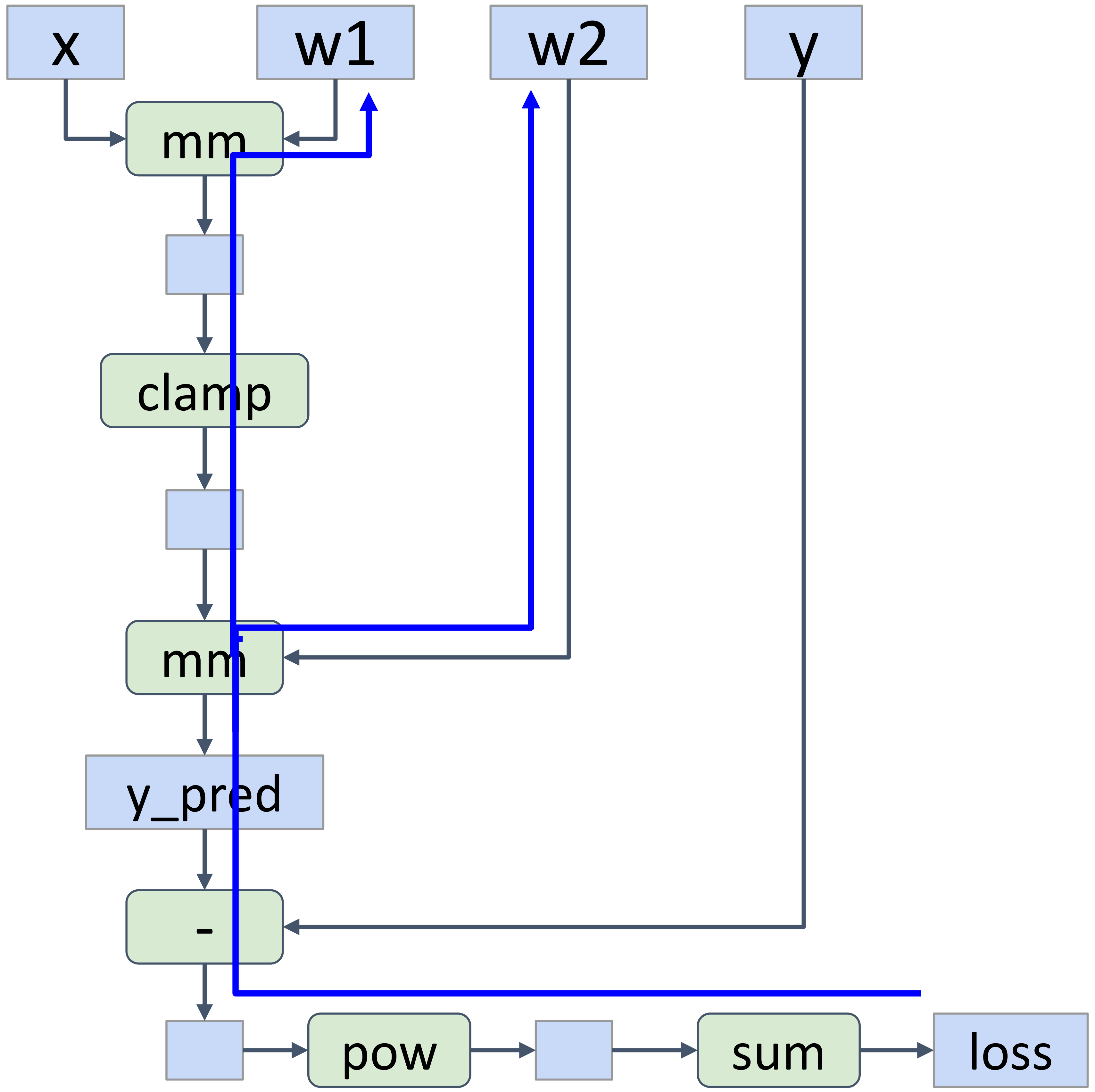
PyTorch: Dynamic Computation Graphs




```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure
AND perform computation

PyTorch: Dynamic Computation Graphs




```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Perform backprop,
throw away graph

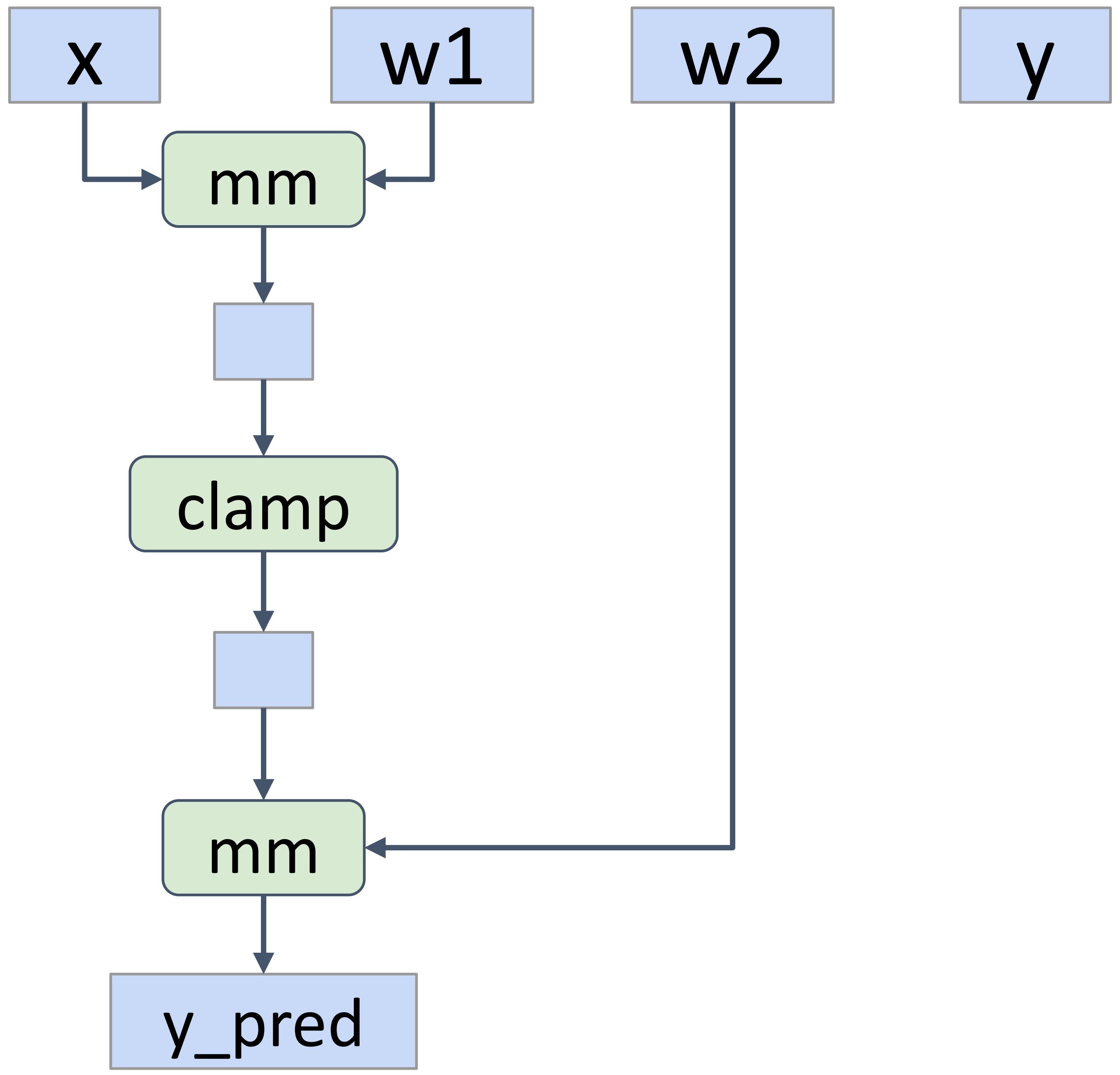
PyTorch: Dynamic Computation Graphs

x w1 w2 y

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Perform backprop, throw away graph

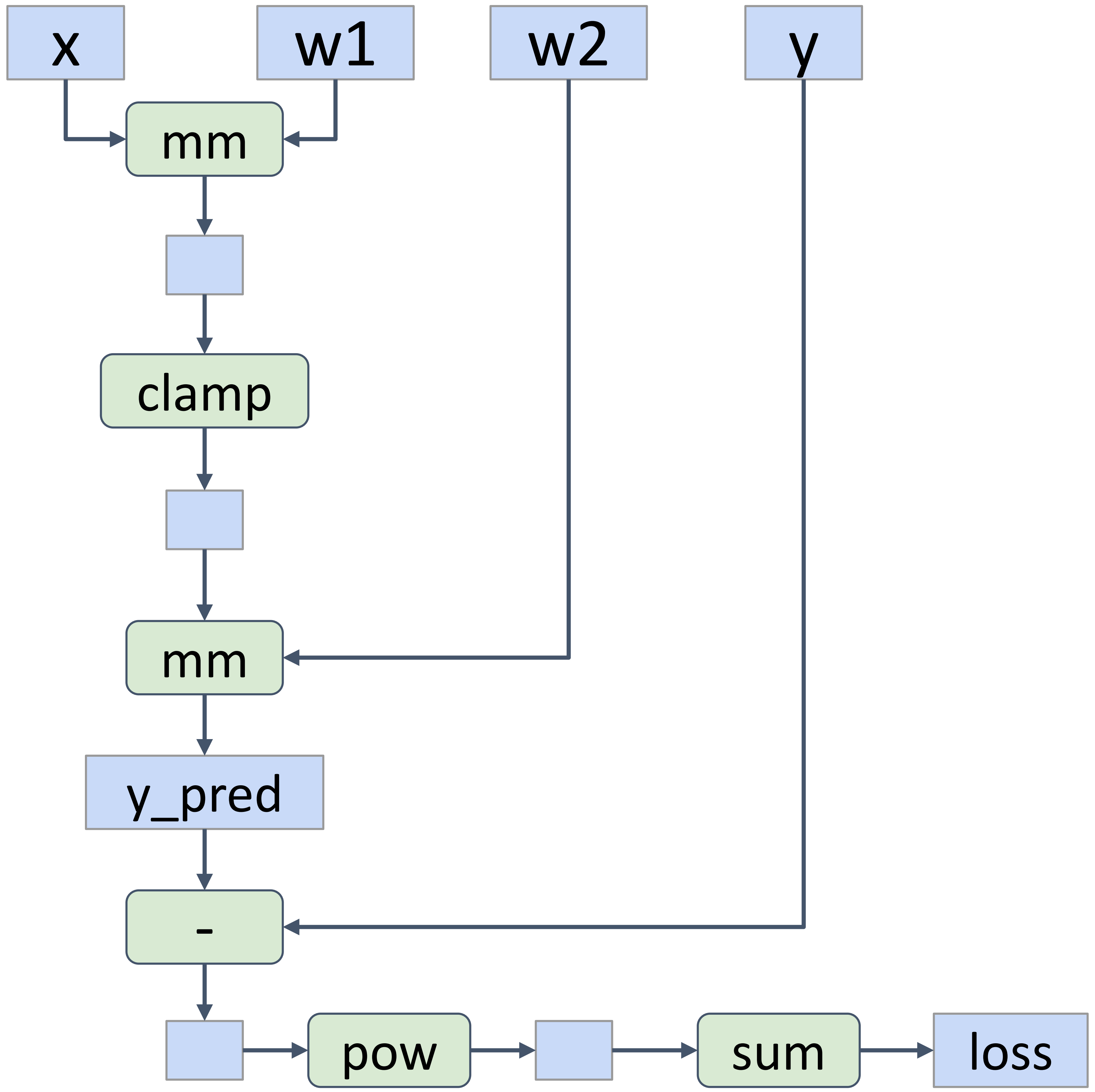
PyTorch: Dynamic Computation Graphs




```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure
AND perform computation

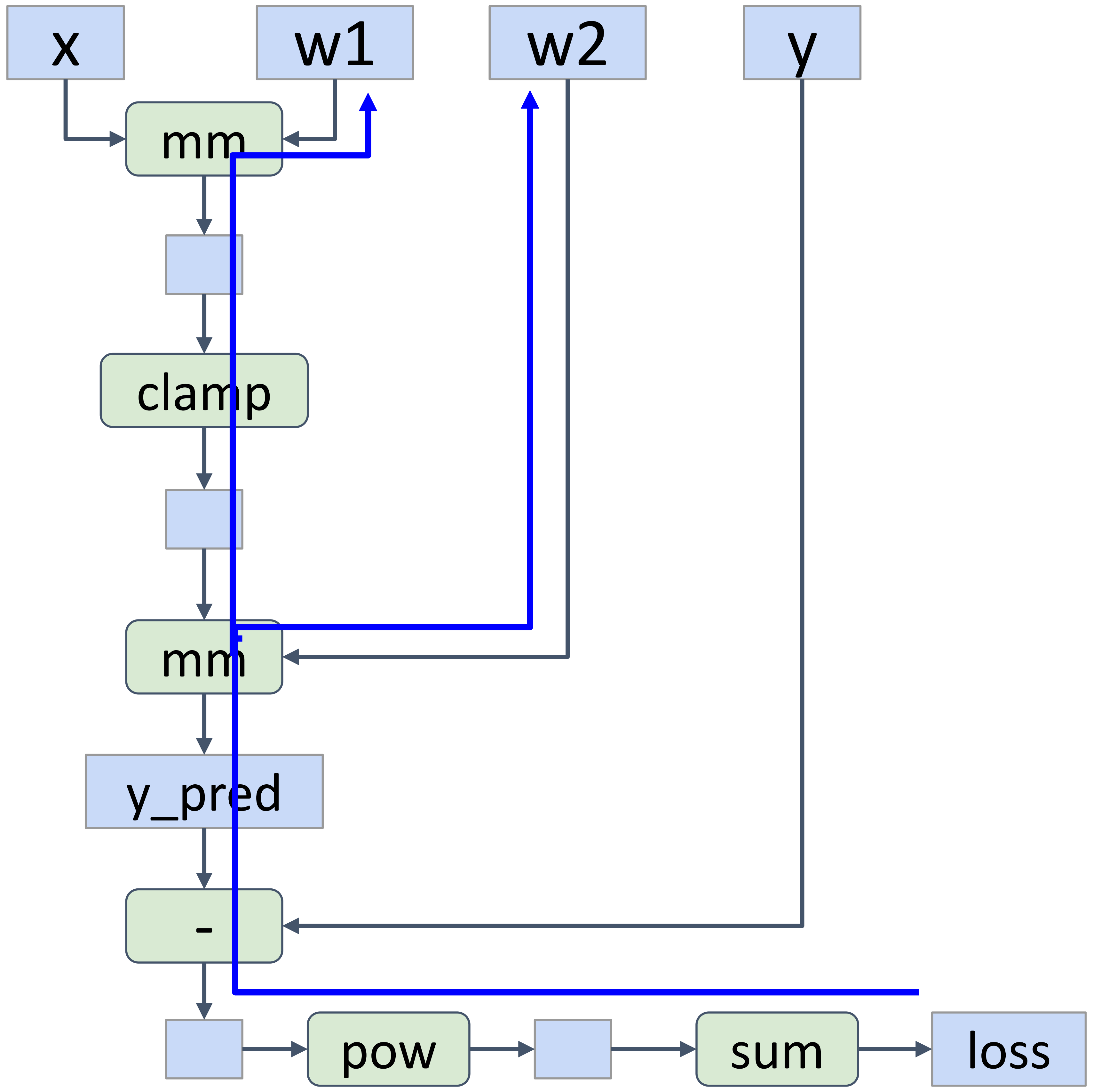
PyTorch: Dynamic Computation Graphs




```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Build graph data structure
AND perform computation

PyTorch: Dynamic Computation Graphs




```python
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2 = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
for t in range(500):
    y_pred = x.mm(w1).clamp(min=0).mm(w2)
    loss = (y_pred - y).pow(2).sum()

    loss.backward()
```

Perform backprop,
throw away graph

PyTorch: Dynamic Computation Graphs

Dynamic graphs let you use regular Python control flow during the forward pass!

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
prev_loss = 5.0
for t in range(500):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  prev_loss = loss.item()
```

PyTorch: Dynamic Computation Graphs

Dynamic graphs let you use regular Python control flow during the forward pass!

Initialize two different weight matrices for second layer

```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
prev_loss = 5.0
for t in range(500):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  prev_loss = loss.item()
```

PyTorch: Dynamic Computation Graphs

Dynamic graphs let you use regular Python control flow during the forward pass!

Decide which one to use at each layer based on loss at previous iteration

(this model doesn't makes sense! Just a simple dynamic example)

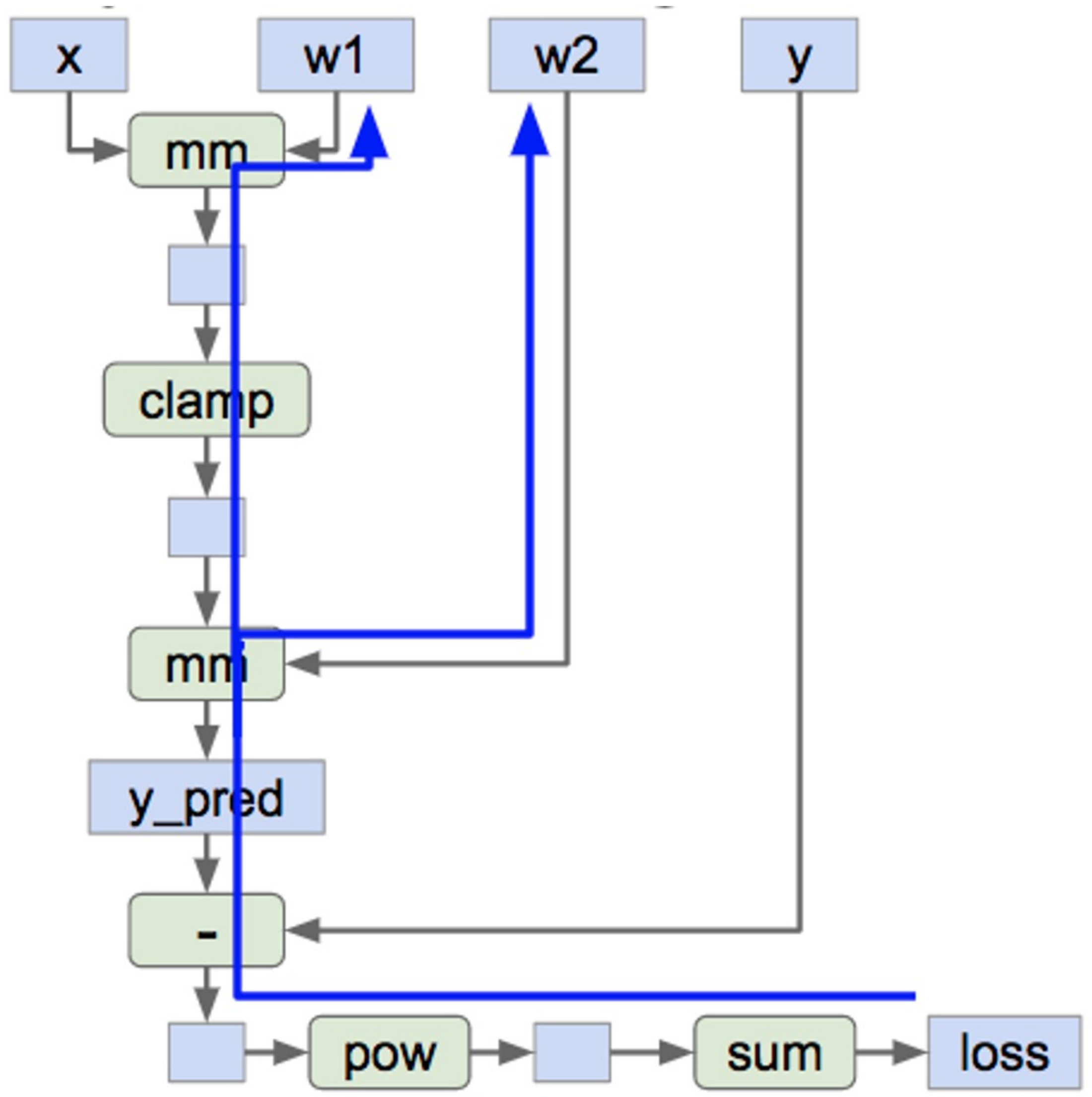
```
import torch

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

learning_rate = 1e-6
prev_loss = 5.0
for t in range(500):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()

  loss.backward()
  prev_loss = loss.item()
```

Alternative: Static Computation Graphs

Alternative: **Static** graphs

Step 1: Build computational graph describing our computation (including finding paths for backprop)

Step 2: Reuse the same graph on every iteration




```
graph = build_graph()

for x_batch, y_batch in loader:
    run_graph(graph, x=x_batch, y=y_batch)
```

Alternative: Static Graphs with JIT

Define model as a Python function

```python
import torch

def model(x, y, w1, w2a, w2b, prev_loss):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()
  return loss

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

graph = torch.jit.script(model)

prev_loss = 5.0
learning_rate = 1e-6
for t in range(500):
  loss = graph(x, y, w1, w2a, w2b, prev_loss)

  loss.backward()
  prev_loss = loss.item()
```

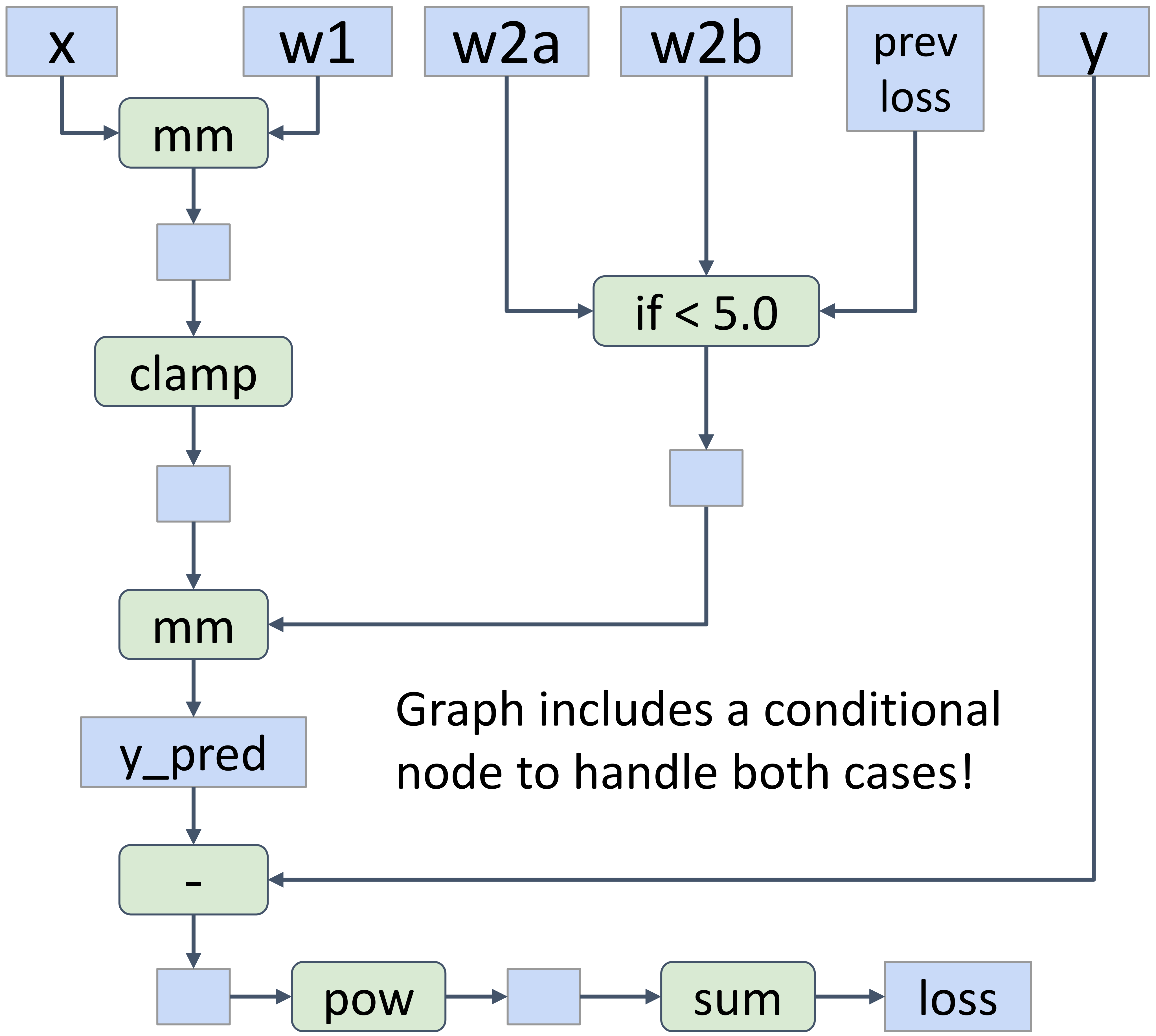
Alternative: Static Graphs with JIT

Just-In-Time compilation: Introspect the source code of the function, **compile** it into a graph object.

Lots of magic here!

```
import torch

def model(x, y, w1, w2a, w2b, prev_loss):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()
  return loss

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

graph = torch.jit.script(model)

prev_loss = 5.0
learning_rate = 1e-6
for t in range(500):
  loss = graph(x, y, w1, w2a, w2b, prev_loss)

  loss.backward()
  prev_loss = loss.item()
```

Alternative: Static Graphs with JIT



Graph includes a conditional node to handle both cases!

```
import torch

def model(x, y, w1, w2a, w2b, prev_loss):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()
  return loss

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

graph = torch.jit.script(model)

prev_loss = 5.0
learning_rate = 1e-6
for t in range(500):
  loss = graph(x, y, w1, w2a, w2b, prev_loss)

  loss.backward()
  prev_loss = loss.item()
```

Alternative: Static Graphs with JIT

Use our compiled graph object at each forward pass

```
import torch

def model(x, y, w1, w2a, w2b, prev_loss):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()
  return loss

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

graph = torch.jit.script(model)

prev_loss = 5.0
learning_rate = 1e-6
for t in range(500):
  loss = graph(x, y, w1, w2a, w2b, prev_loss)

  loss.backward()
  prev_loss = loss.item()
```

Alternative: Static Graphs with JIT

Even easier: add **annotation** to function, Python function compiled to a graph when it is defined

Calling function uses graph

```
import torch

@torch.jit.script
def model(x, y, w1, w2a, w2b, prev_loss):
  w2 = w2a if prev_loss < 5.0 else w2b
  y_pred = x.mm(w1).clamp(min=0).mm(w2)
  loss = (y_pred - y).pow(2).sum()
  return loss

N, D_in, H, D_out = 64, 1000, 100, 10
x = torch.randn(N, D_in)
y = torch.randn(N, D_out)
w1 = torch.randn(D_in, H, requires_grad=True)
w2a = torch.randn(H, D_out, requires_grad=True)
w2b = torch.randn(H, D_out, requires_grad=True)

prev_loss = 5.0
learning_rate = 1e-6
for t in range(500):
  loss = model(x, y, w1, w2a, w2b, prev_loss)

  loss.backward()
  prev_loss = loss.item()
```

Static vs Dynamic Graphs: Optimization

With static graphs, framework can **optimize** the graph for you before it runs!

The graph you wrote

Conv
ReLU
Conv
ReLU
Conv
ReLU

Equivalent graph with **fused operations**

Conv+ReLU
Conv+ReLU
Conv+ReLU

Static vs Dynamic Graphs: Optimization

Static

Once graph is built, can **serialize** it and run it without the code that built the graph!

e.g. train model in Python, deploy in C++

Dynamic

Graph building and execution are intertwined, so always need to keep code around

Static vs Dynamic Graphs: Optimization

Static

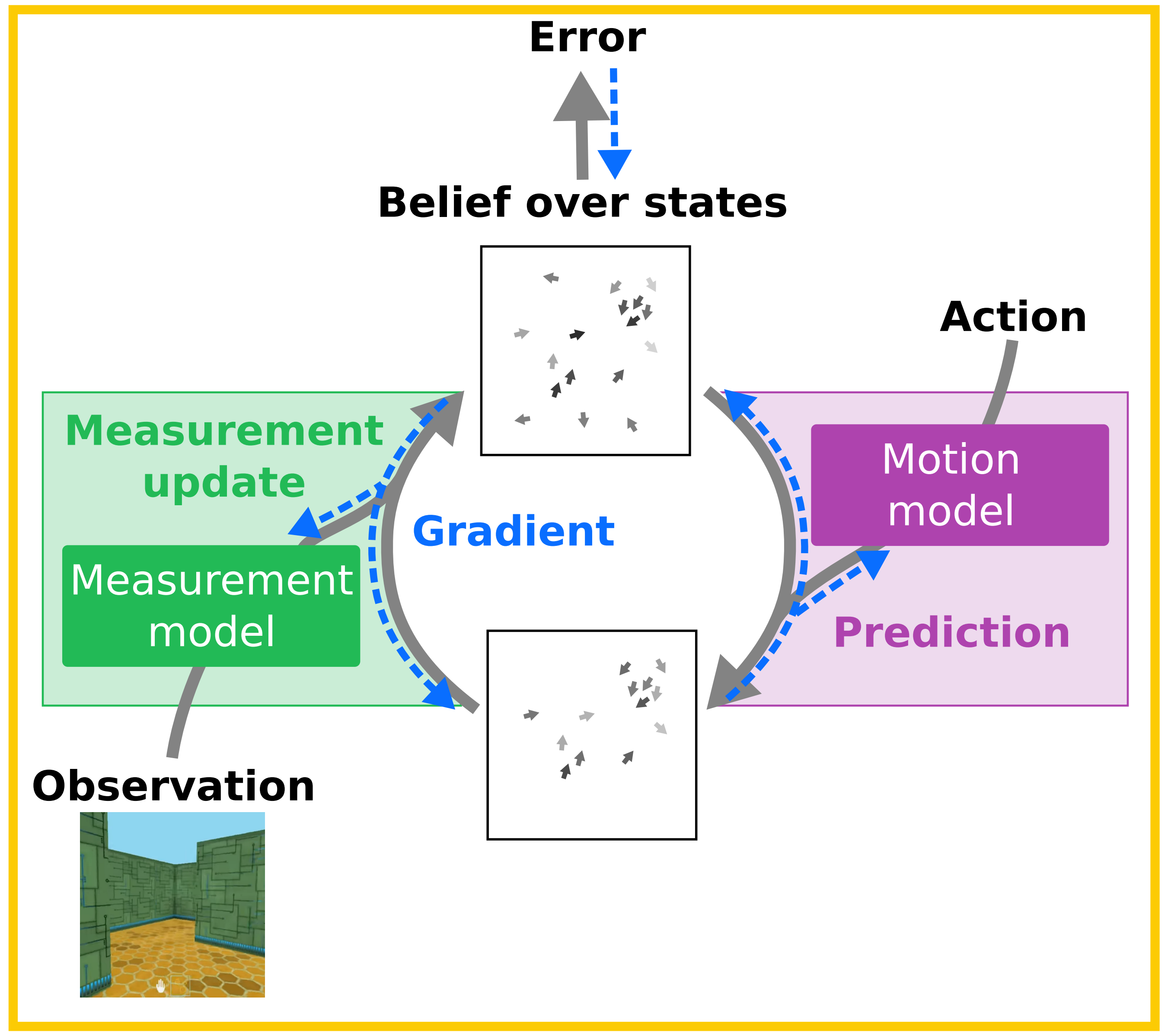
Lots of indirection between the code you write and the code that runs – can be hard to debug, benchmark, etc

Dynamic

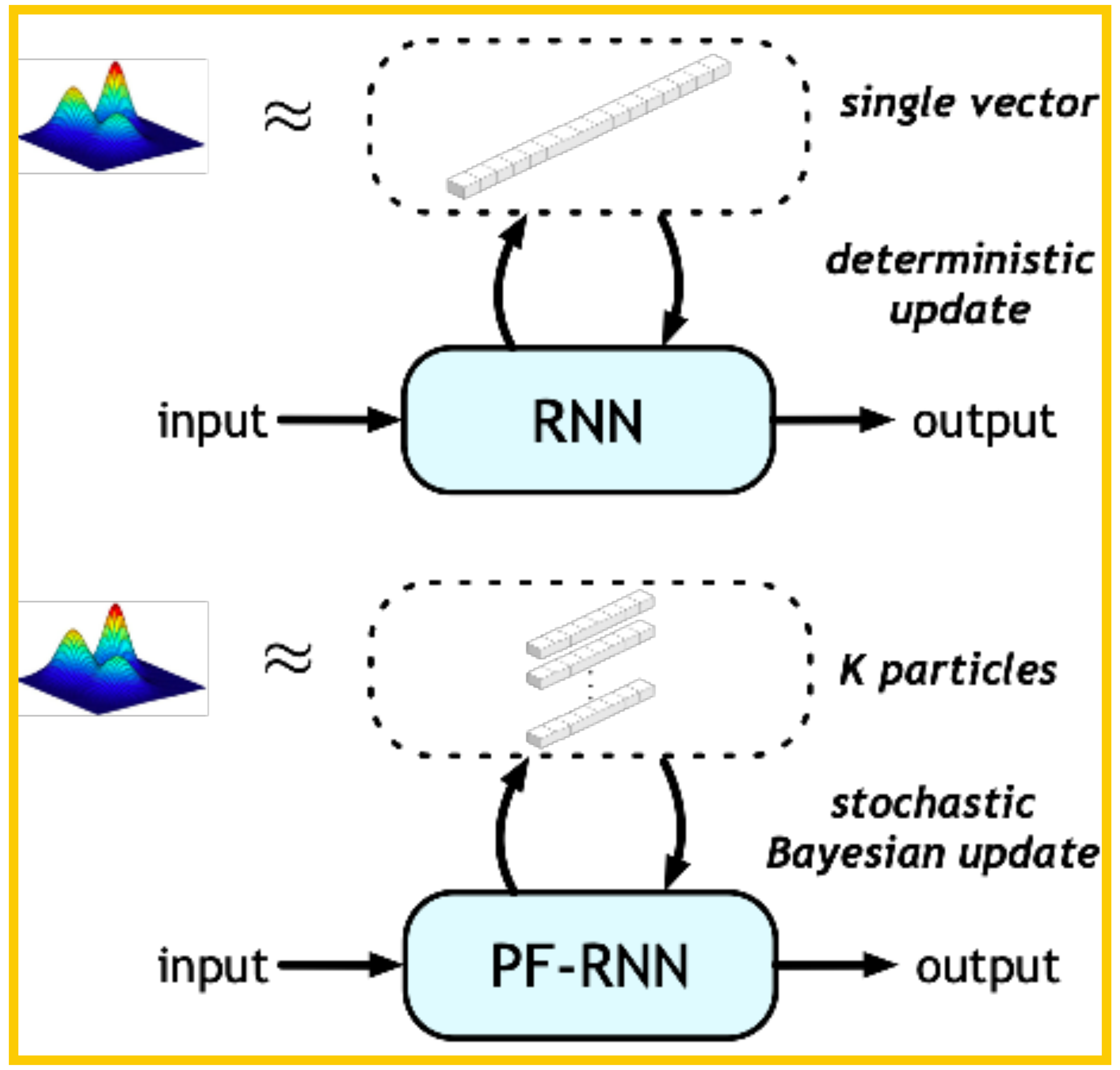
The code you write is the code that runs! Easy to reason about, debug, profile, etc

Dynamic Graph Applications

Model structure depends on the input:
- Recurrent Networks
- Recursive Networks



[1] Ma et al., RSS 2018

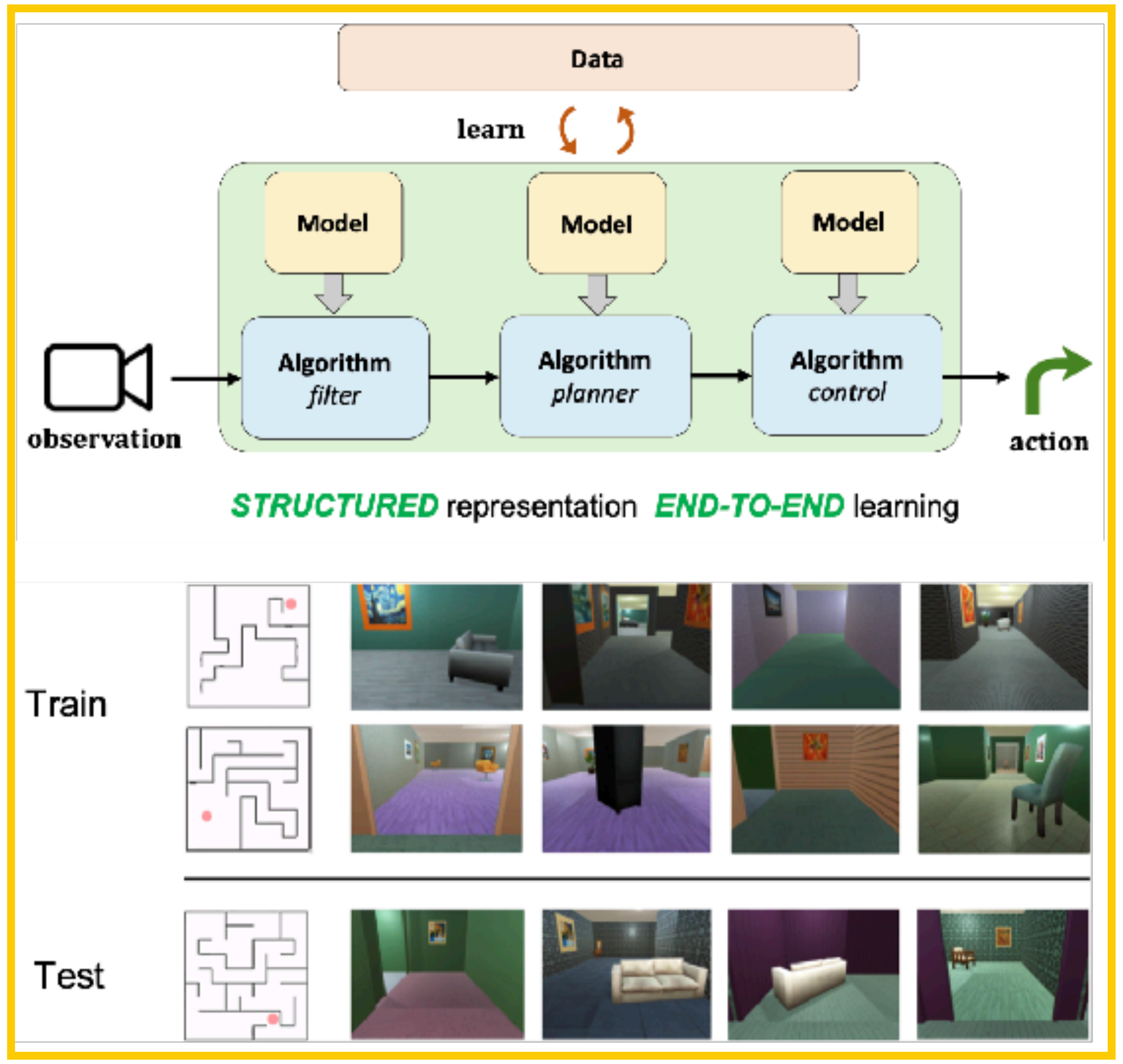


[2] Ma et al., AAAI 2020

[1] Rico Jonschkowski, Divyam Rastogi, Oliver Brock. "Differentiable Particle Filters: End-to-End Learning with Algorithmic Priors" RSS, 2018
[2] Xiao Ma, Peter Karkus, David Hsu, Wee Sun Lee. "Particle Filter Recurrent Neural Networks" AAAI, 2020.

Dynamic Graph Applications

Model structure depends on the input:
- Recurrent Networks
- Recursive Networks
- Modular Networks



[1] Karkus et al., RSS 2019

[1] Peter Karkus, Xiao Ma, David Hsu, Leslie Pack Kaelbling, Wee Sun Lee, Tomas Lozano-Perez. "Differentiable Algorithm Networks for Composable Robot Learning" RSS, 2019

Dynamic Graph Applications

Model structure depends on the input:

- Recurrent Networks
- Recursive Networks
- Modular Networks
- (Your idea here!)

Final Project!

TensorFlow

TensorFlow: Versions

TensorFlow 1.0

- Final release: 1.15.3
- Default: **static graphs**
- Optional: dynamic graphs (eager mode)

TensorFlow 2.0

- Current release: 2.8.0
    - Released 2/2/2022
- Default**: dynamic graphs**
- Optional: static graphs

TensorFlow 1.0: Static Graphs

```
import numpy as np
import tensorflow as tf
```

(Assume imports at the top of each snippet)

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])

with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                   feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

TensorFlow 1.0: Static Graphs

First **define** computational graph

```
N, D, H = 64, 1000, 100
x = tf.placeholder(tf.float32, shape=(N, D))
y = tf.placeholder(tf.float32, shape=(N, D))
w1 = tf.placeholder(tf.float32, shape=(D, H))
w2 = tf.placeholder(tf.float32, shape=(H, D))

h = tf.maximum(tf.matmul(x, w1), 0)
y_pred = tf.matmul(h, w2)
diff = y_pred - y
loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

grad_w1, grad_w2 = tf.gradients(loss, [w1, w2])
```

Then **run** the graph many times

```
with tf.Session() as sess:
    values = {x: np.random.randn(N, D),
              w1: np.random.randn(D, H),
              w2: np.random.randn(H, D),
              y: np.random.randn(N, D),}
    out = sess.run([loss, grad_w1, grad_w2],
                   feed_dict=values)
    loss_val, grad_w1_val, grad_w2_val = out
```

TensorFlow 2.0: Dynamic Graphs

Create TensorFlow Tensors for data and weights

Weights need to be wrapped in tf.Variable so we can mutate them

```
import tensorflow as tf

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
```

TensorFlow 2.0: Dynamic Graphs

Scope forward pass under a GradientTape to tell TensorFlow to start building a graph

```
import tensorflow as tf

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
```

TensorFlow 2.0: Dynamic Graphs

Scope forward pass under a GradientTape to tell TensorFlow to start building a graph

```
import tensorflow as tf

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
```

In PyTorch, all ops build graph by default; **opt out** via torch.no_grad
In Tensorflow, ops do not build graph by default; **opt in** via GradientTape

TensorFlow 2.0: Dynamic Graphs

Ask the tape to compute gradients

```
import tensorflow as tf

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
```

TensorFlow 2.0: Dynamic Graphs

```
import tensorflow as tf

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
```

Gradient descent step, update weights

TensorFlow 2.0: Static Graphs

Define a function that implements forward, backward, and update

Annotating with tf.function will compile the function into a graph! (similar to torch.jit.script)

```
@tf.function
def step(x, y, w1, w2):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
  return loss

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  loss = step(x, y, w1, w2)
```

TensorFlow 2.0: Static Graphs

Define a function that implements forward, backward, and update

Annotating with tf.function will compile the function into a graph! (similar to torch.jit.script)

(note TF graph can include gradient computation and update, unlike PyTorch)

```
@tf.function
def step(x, y, w1, w2):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
  return loss

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  loss = step(x, y, w1, w2)
```

TensorFlow 2.0: Static Graphs

```
@tf.function
def step(x, y, w1, w2):
  with tf.GradientTape() as tape:
    h = tf.maximum(tf.matmul(x, w1), 0)
    y_pred = tf.matmul(h, w2)
    diff = y_pred - y
    loss = tf.reduce_mean(tf.reduce_sum(diff ** 2, axis=1))

  grad_w1, grad_w2 = tape.gradient(loss, [w1, w2])

  w1.assign(w1 - learning_rate * grad_w1)
  w2.assign(w2 - learning_rate * grad_w2)
  return loss

N, Din, H, Dout = 16, 1000, 100, 10

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))
w1 = tf.Variable(tf.random.normal((Din, H)))
w2 = tf.Variable(tf.random.normal((H, Dout)))

learning_rate = 1e-6
for t in range(1000):
  loss = step(x, y, w1, w2)
```

Call the compiled step function in the training loop

Keras: High-level API

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))
params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

for t in range(1000):
  with tf.GradientTape() as tape:
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
  grads = tape.gradient(loss, params)
  opt.apply_gradients(zip(grads, params))
```

Keras: High-level API

Object-oriented API: build the model as a stack of layers

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))
params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

for t in range(1000):
  with tf.GradientTape() as tape:
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
  grads = tape.gradient(loss, params)
  opt.apply_gradients(zip(grads, params))
```

Keras: High-level API

Keras gives you common loss functions and optimization algorithms

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))
params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

for t in range(1000):
  with tf.GradientTape() as tape:
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
  grads = tape.gradient(loss, params)
  opt.apply_gradients(zip(grads, params))
```

Keras: High-level API

Forward pass:
Compute loss,
build graph

Backward pass:
compute gradients

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))
params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

for t in range(1000):
  with tf.GradientTape() as tape:
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
  grads = tape.gradient(loss, params)
  opt.apply_gradients(zip(grads, params))
```

Keras: High-level API

```
import tensorflow as tf
from tensorflow.keras.models import Sequential
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params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

for t in range(1000):
  with tf.GradientTape() as tape:
    y_pred = model(x)
    loss = loss_fn(y_pred, y)
  grads = tape.gradient(loss, params)
  opt.apply_gradients(zip(grads, params))
```

Optimizer object updates parameters

Keras: High-level API

Define a function that returns the loss

```python
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))

params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

def step():
  y_pred = model(x)
  loss = loss_fn(y_pred, y)
  return loss

for t in range(1000):
  opt.minimize(step, params)
```

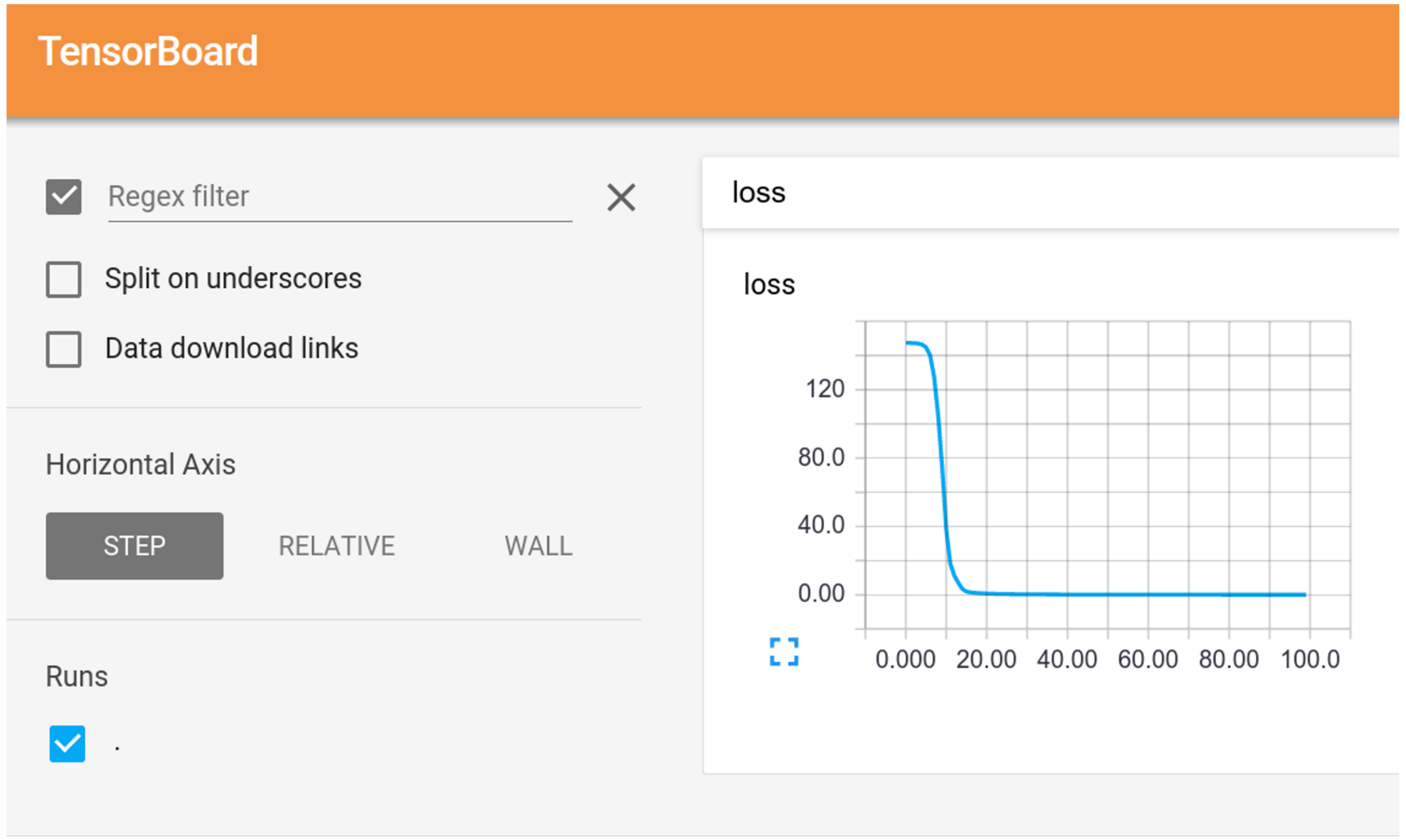
Keras: High-level API

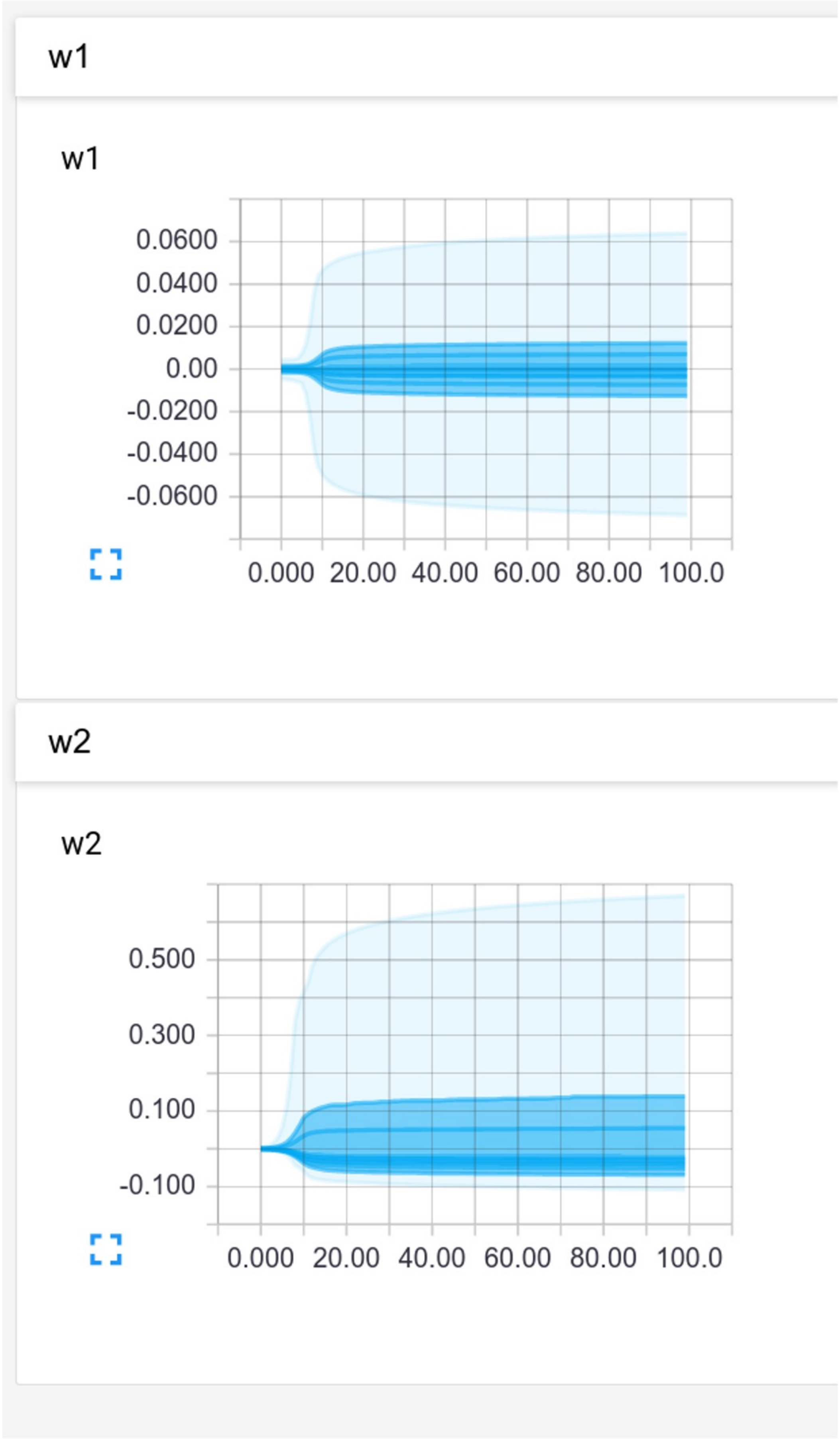
```
import tensorflow as tf
from tensorflow.keras.models import Sequential
from tensorflow.keras.layers import InputLayer, Dense

N, Din, H, Dout = 16, 1000, 100, 10

model = Sequential()
model.add(InputLayer(input_shape=(Din,)))
model.add(Dense(units=H, activation='relu'))
model.add(Dense(units=Dout))

params = model.trainable_variables

loss_fn = tf.keras.losses.MeanSquaredError()
opt = tf.keras.optimizers.SGD(learning_rate=1e-6)

x = tf.random.normal((N, Din))
y = tf.random.normal((N, Dout))

def step():
  y_pred = model(x)
  loss = loss_fn(y_pred, y)
  return loss

for t in range(1000):
  opt.minimize(step, params)
```

Optimizer computes gradients and updates parameters

TensorBoard

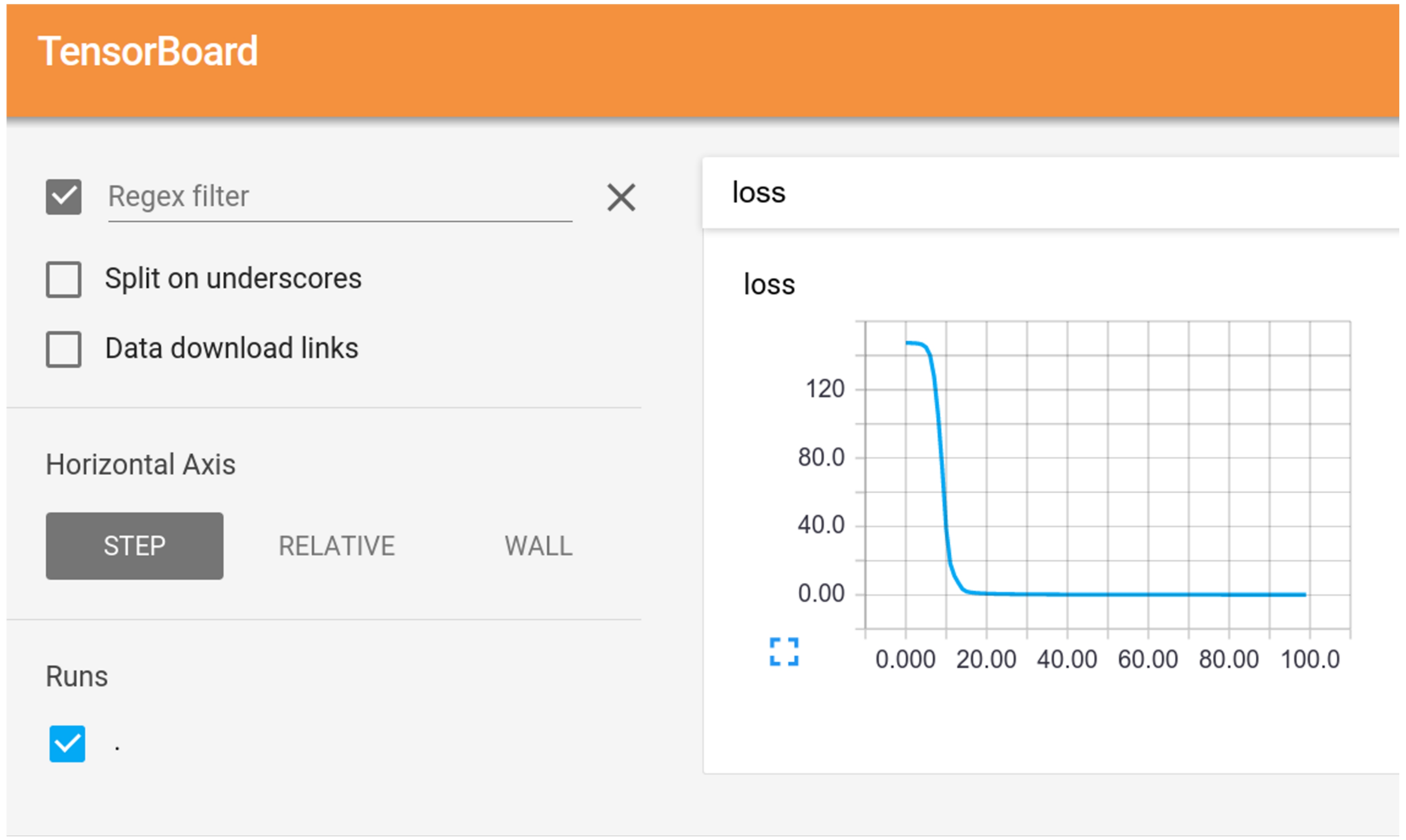
Add logging to code to record loss, stats, etc
Run server and get pretty graphs!

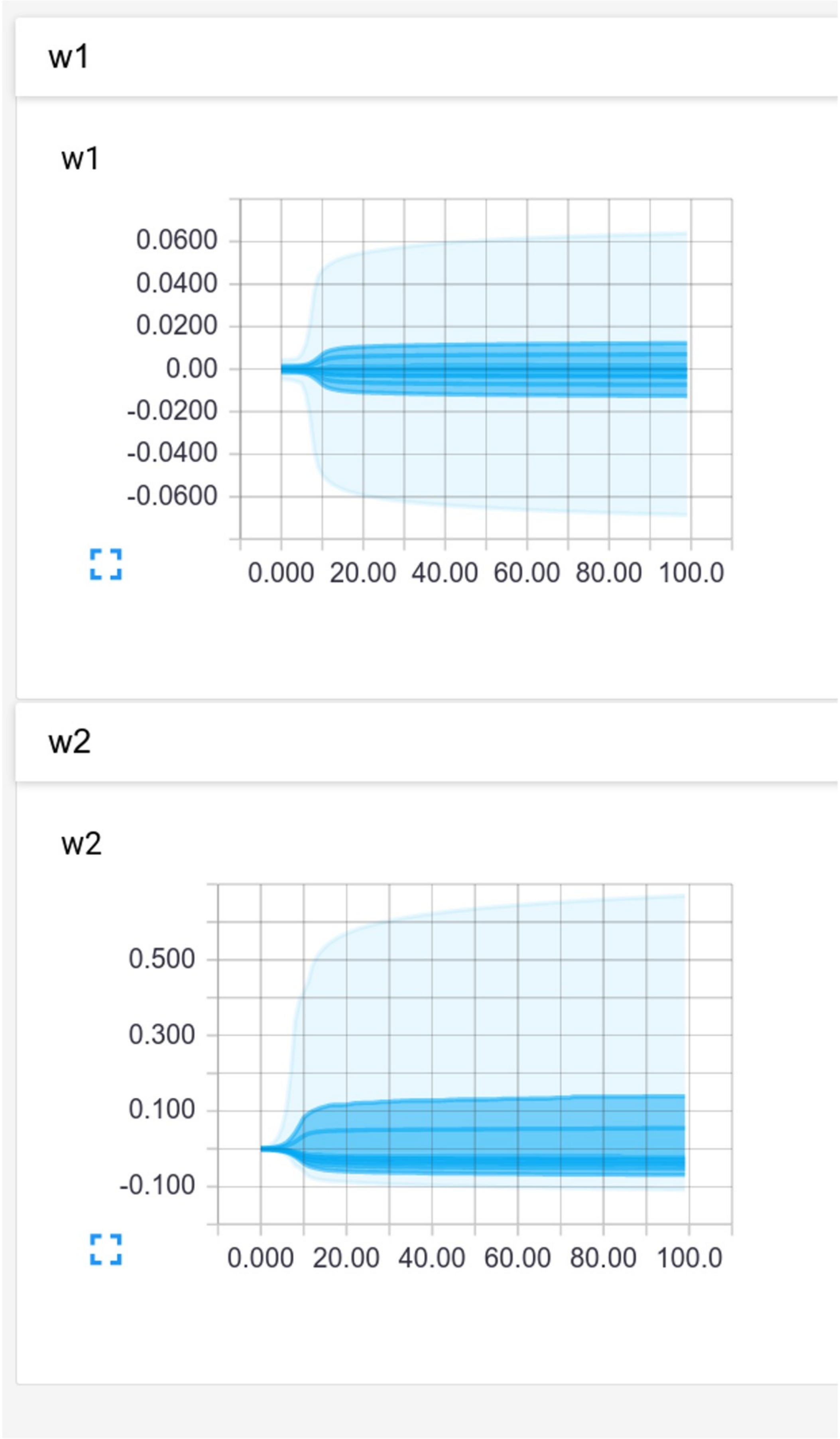




TensorBoard

Also works with PyTorch!





PyTorch vs TensorFlow

PyTorch
- My personal favorite
- Clean, imperative API
- Easy dynamic graphs for debugging
- JIT allows static graphs for production
- Hard / inefficient to use on TPUs
- Not easy to deploy on mobile

TensorFlow 1.0
- Static graphs by default
- Can be confusing to debug
- API a bit messy

TensorFlow 2.0
- Dynamic by default
- Standardized on Keras API
- API still confusing

Summary: Deep Learning Software

Static Graphs vs **Dynamic Graphs**

PyTorch vs **TensorFlow**

Next Time: Object Detectors

DeepRob

Lecture 11
Deep Learning Software
University of Michigan and University of Minnesota