
PYTORCH

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What is PyTorch?

What is PyTorch?

automatic differentiation engine

Ndarray library with GPU support

gradient based optimization package

Utilities (data loading, etc.)

Deep Learning

Reinforcement Learning

Numpy-alternative

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]
```

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
```

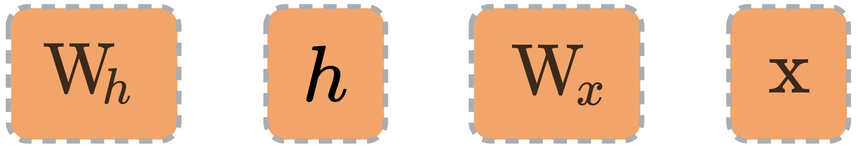
automatic differentiation engine

for deep learning and reinforcement learning

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

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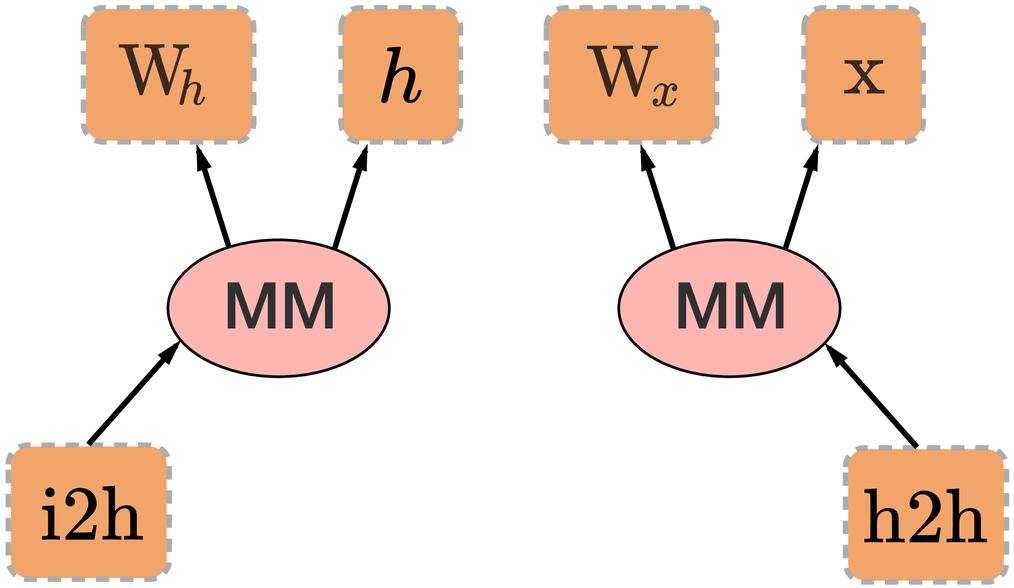
W_h = Variable(torch.randn(20, 20))
W_x = Variable(torch.randn(20, 10))

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



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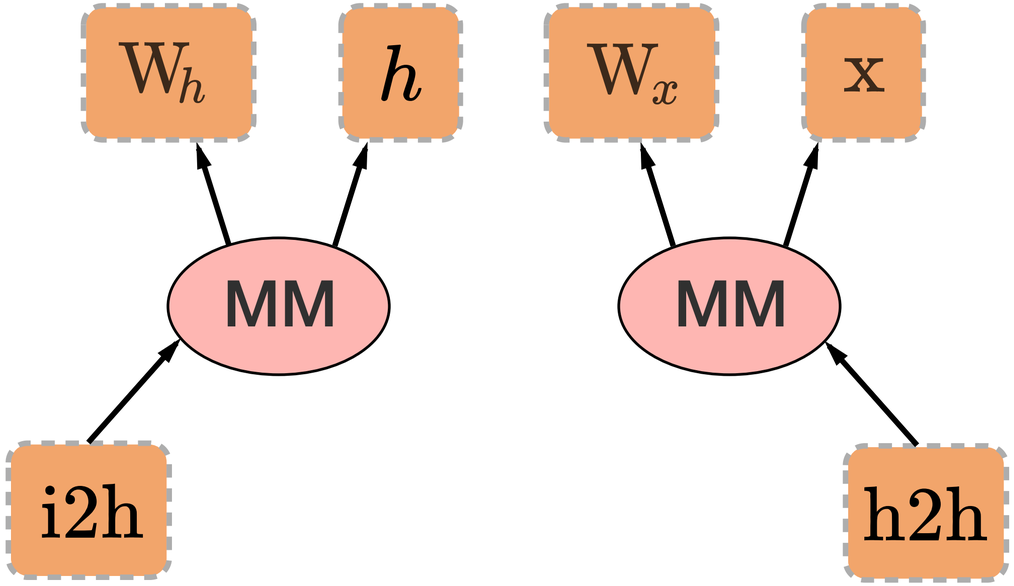
W_x = Variable(torch.randn(20, 10))

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



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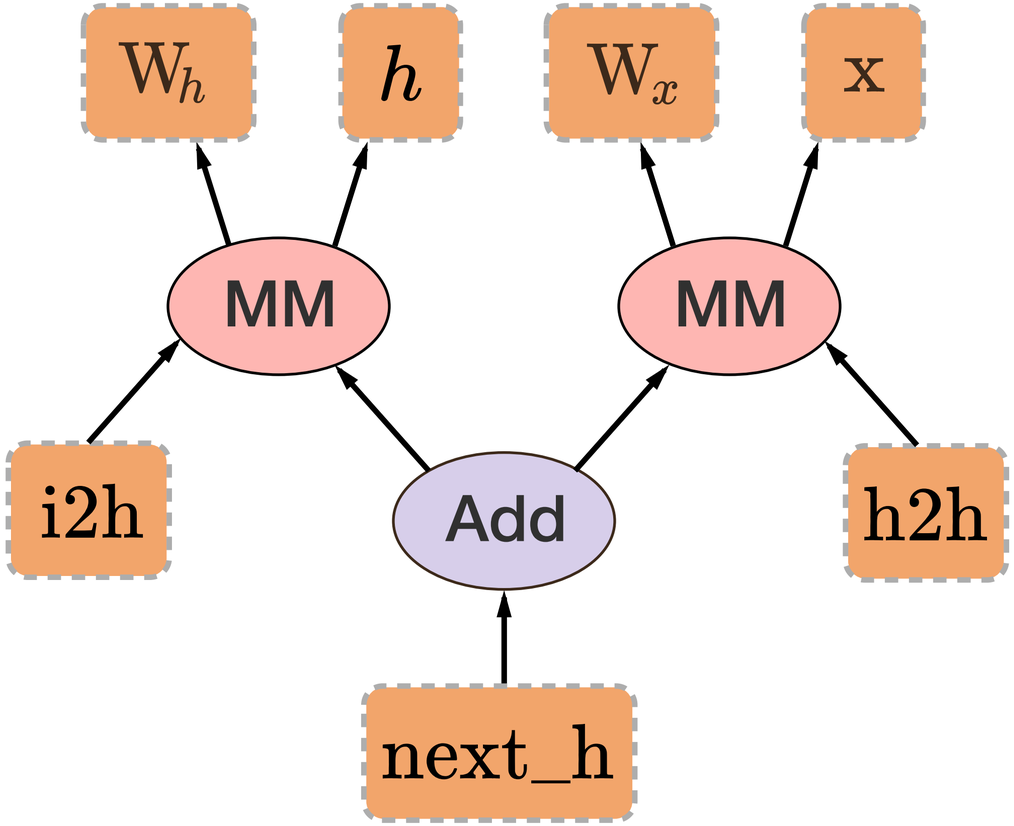

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i2h = torch.mm(W_x, x.t())
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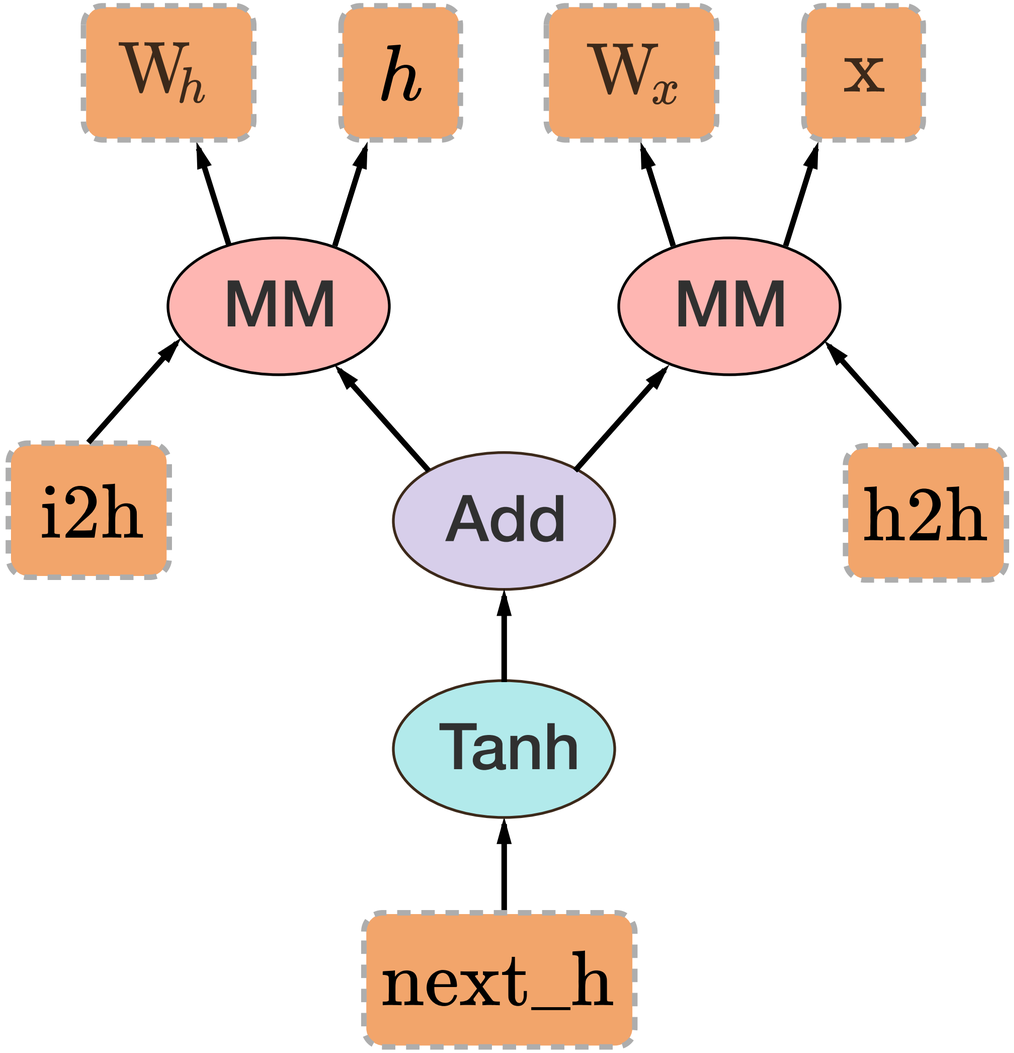
next_h = i2h + h2h
next_h = next_h.tanh()
```



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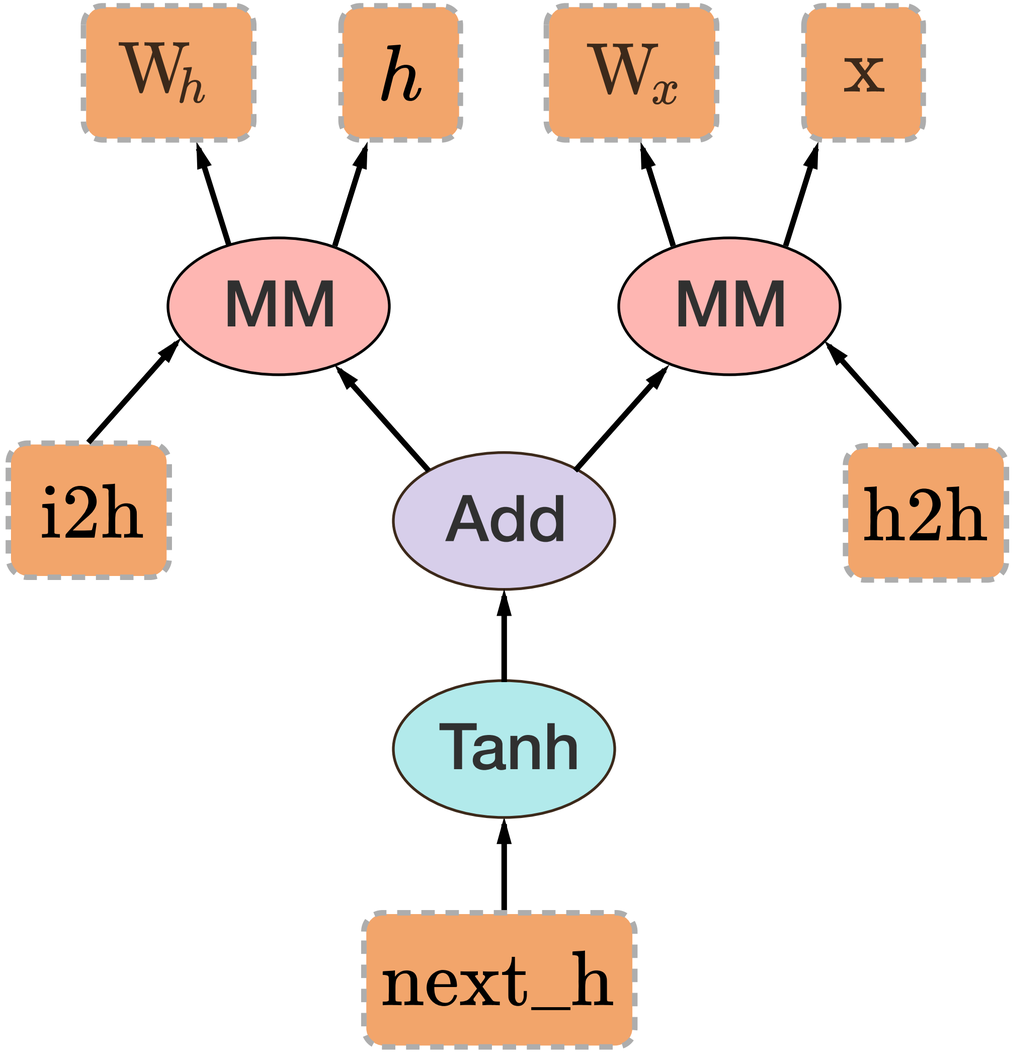
i2h = torch.mm(W_x, x.t())
h2h = torch.mm(W_h, prev_h.t())
next_h = i2h + h2h
next_h = next_h.tanh()

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



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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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()
```

Work items in practice

Writing Dataset loaders

Building models

Implementing Training loop

Checkpointing models

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

Writing Data Loaders

- every dataset is slightly differently formatted

Writing Data Loaders

- every dataset is slightly differently formatted
- have to be preprocessed and normalized differently

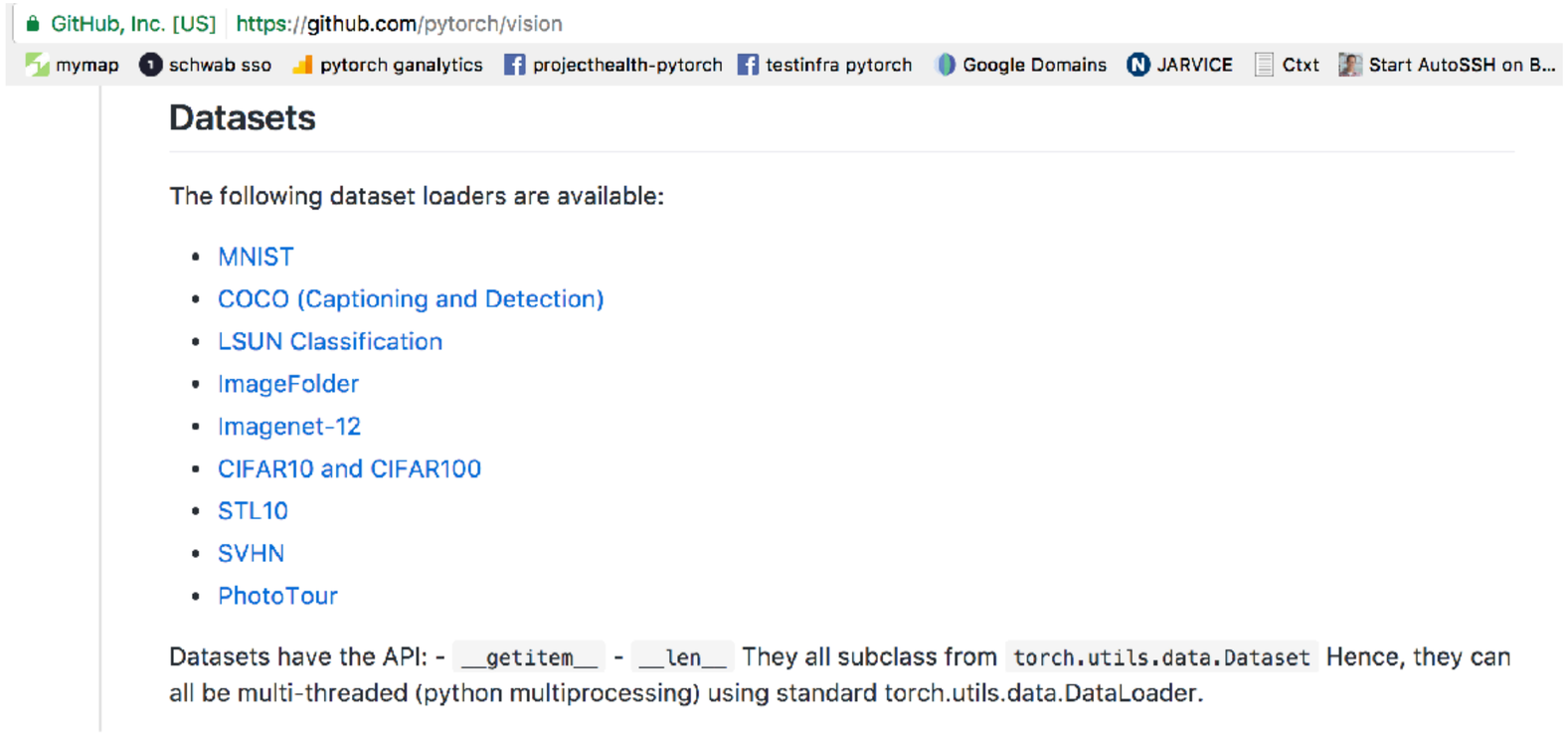
Writing Data Loaders

- every dataset is slightly differently formatted
- have to be preprocessed and normalized differently
- need a multithreaded Data loader to feed GPUs fast enough

Writing Data Loaders

PyTorch solution:

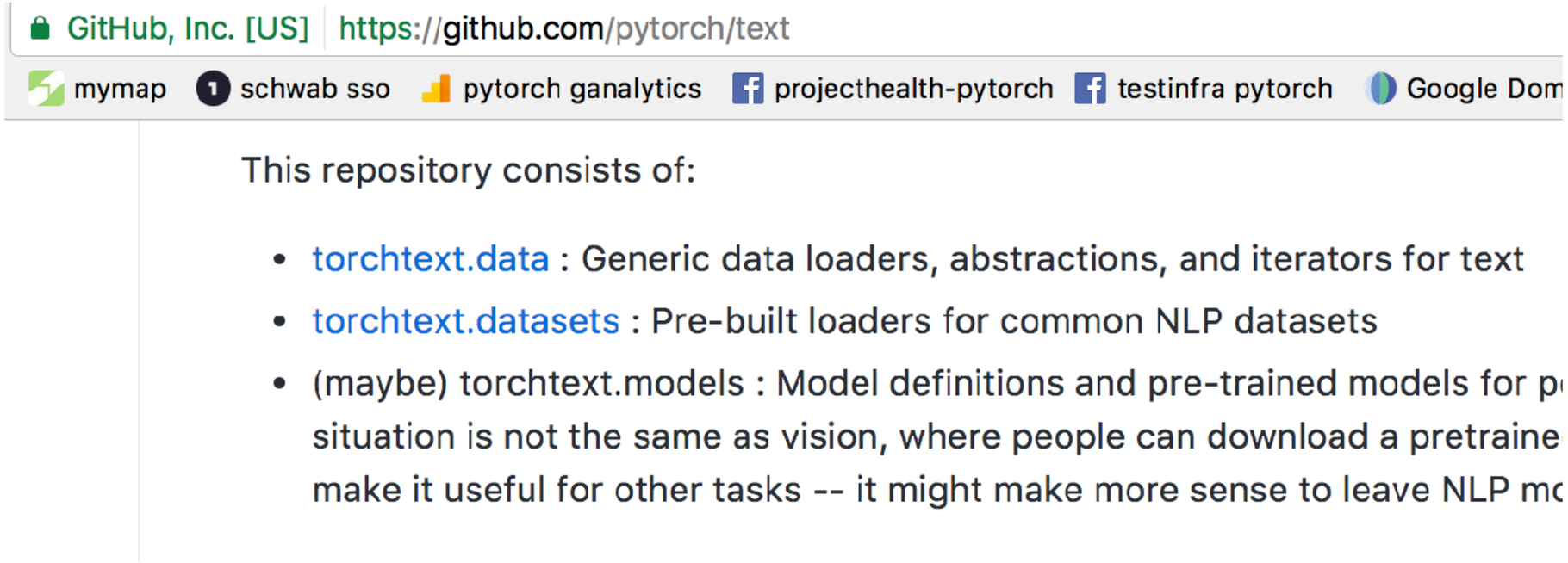
- share data loaders across the community!



Writing Data Loaders

PyTorch solution:

- share data loaders across the community!



Writing Data Loaders

PyTorch solution:

- use regular Python to write Datasets:

  leverage existing Python code

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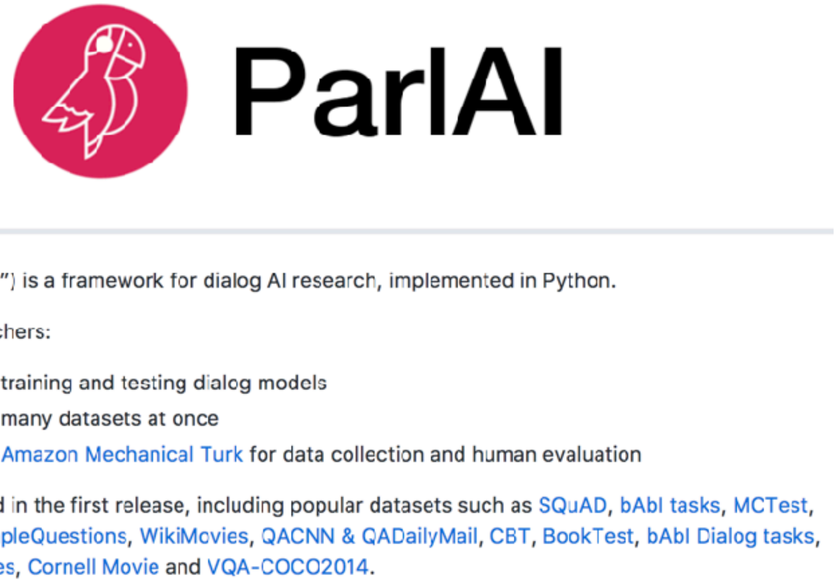
  Example: ParlAI



Writing Data Loaders

PyTorch solution:

- Code in practice

Writin

PyTorch

- Code in p

```
57  if opt.dataset in ['imagenet', 'folder', 'lfw']:
58      # folder dataset
59      dataset = dset.ImageFolder(root=opt.dataroot,
60                                 transform=transforms.Compose([
61                                     transforms.Scale(opt.imageSize),
62                                     transforms.CenterCrop(opt.imageSize),
63                                     transforms.ToTensor(),
64                                     transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
65                                 ]))
66  elif opt.dataset == 'lsun':
67      dataset = dset.LSUN(db_path=opt.dataroot, classes=['bedroom_train'],
68                          transform=transforms.Compose([
69                              transforms.Scale(opt.imageSize),
70                              transforms.CenterCrop(opt.imageSize),
71                              transforms.ToTensor(),
72                              transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
73                          ]))
74  elif opt.dataset == 'cifar10':
75      dataset = dset.CIFAR10(root=opt.dataroot, download=True,
76                             transform=transforms.Compose([
77                                 transforms.Scale(opt.imageSize),
78                                 transforms.ToTensor(),
79                                 transforms.Normalize((0.5, 0.5, 0.5), (0.5, 0.5, 0.5)),
80                             ])
81      )
82  assert dataset
83  dataloader = torch.utils.data.DataLoader(dataset, batch_size=opt.batchSize,
84                                           shuffle=True, num_workers=int(opt.workers))
```

Writing Da

PyTorch soluti

- Code in practic

```
def __init__(self, root, annFile, transform=None, target_transform=None):
    from pycocotools.coco import COCO
    self.root = os.path.expanduser(root)
    self.coco = COCO(annFile)
    self.ids = list(self.coco.imgs.keys())
    self.transform = transform
    self.target_transform = target_transform

def __getitem__(self, index):
    """
    Args:
        index (int): Index

    Returns:
        tuple: Tuple (image, target). target is a list of captions for the image.
    """
    coco = self.coco
    img_id = self.ids[index]
    ann_ids = coco.getAnnIds(imgIds=img_id)
    anns = coco.loadAnns(ann_ids)
    target = [ann['caption'] for ann in anns]

    path = coco.loadImgs(img_id)[0]['file_name']

    img = Image.open(os.path.join(self.root, path)).convert('RGB')
    if self.transform is not None:
        img = self.transform(img)

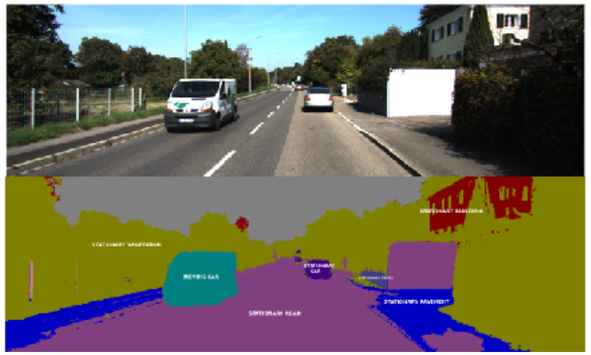
    if self.target_transform is not None:
        target = self.target_transform(target)

    return img, target

def __len__(self):
    return len(self.ids)
```

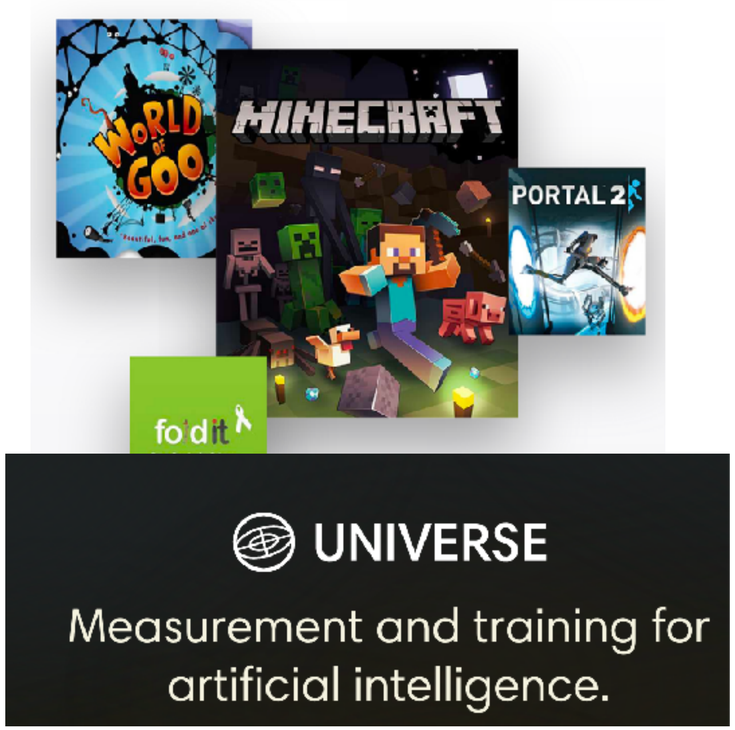
Rese
Work

Interfacing with environments



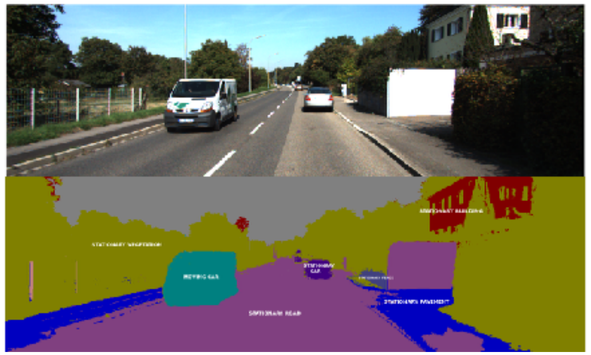
Cars

Video games



Internet

Interfacing with environments



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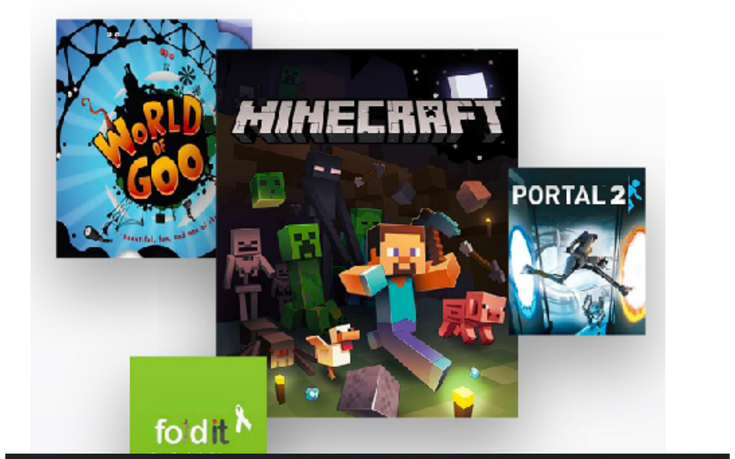
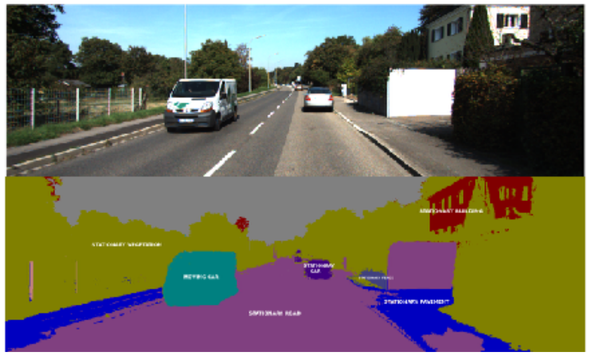


Pretty much every environment provides a Python API

Interfacing with environments



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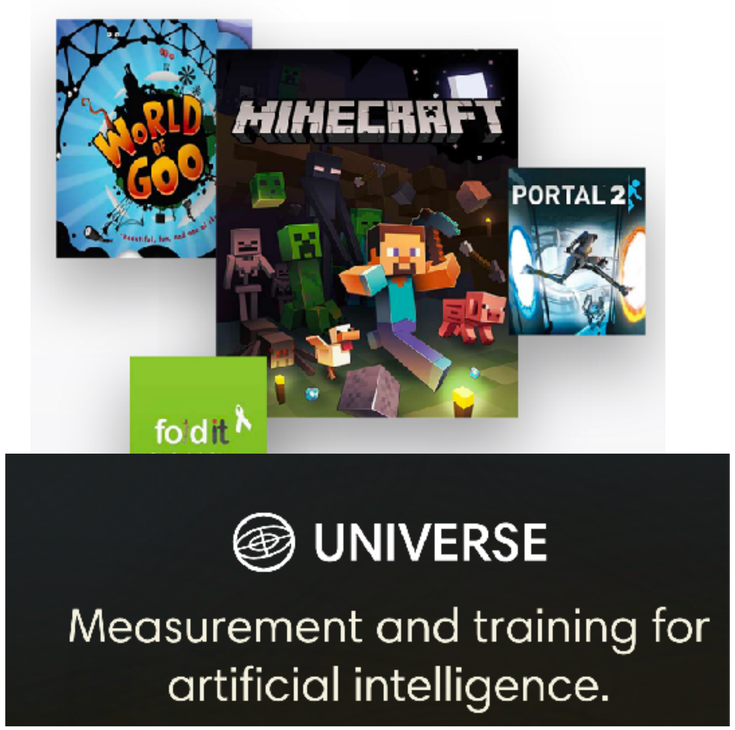

Natively interact with the environment directly

Debugging

- PyTorch is a Python extension

Debugging

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

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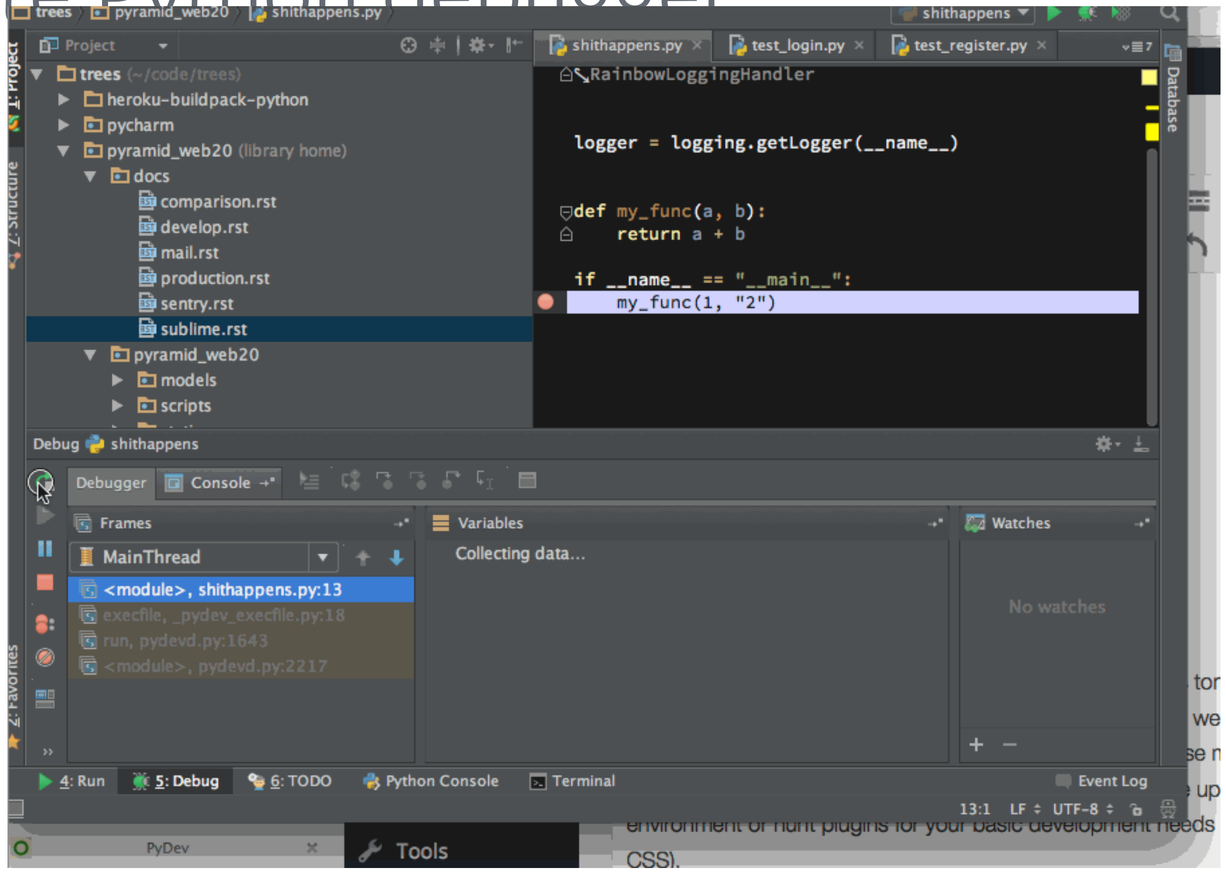

Debugging

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- 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

SNAKEVIZ

← PREVIOUS NEXT → G

SnakeViz
Installation
Starting SnakeViz
Generating Profiles
Interpreting Results
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Notes
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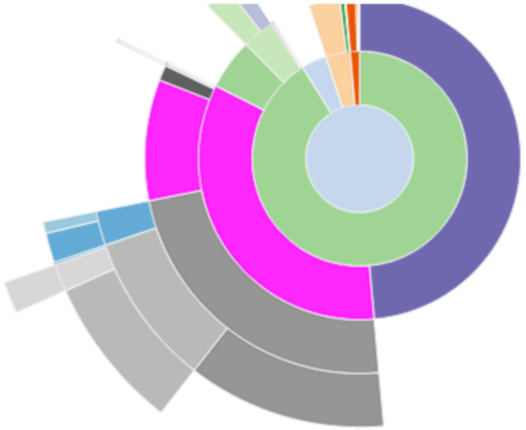
FUNCTION INFO

Placing your cursor over an arc will highlight that arc and any other visible instances of the same function call. It also display a list of information to the left of the sunburst.

Name:
filter
Cumulative Time:
0.000294 s (31.78 %)
File:
fnmatch.py
Line:
48
Directory:
/Users/jiffyclub/miniconda3/envs/snakevizdev/lib/python3.4/



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
```

Compilation Time

- PyTorch is written for the impatient

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- Absolutely no compilation time when writing your scripts whatsoever
- All core kernels are pre-compiled

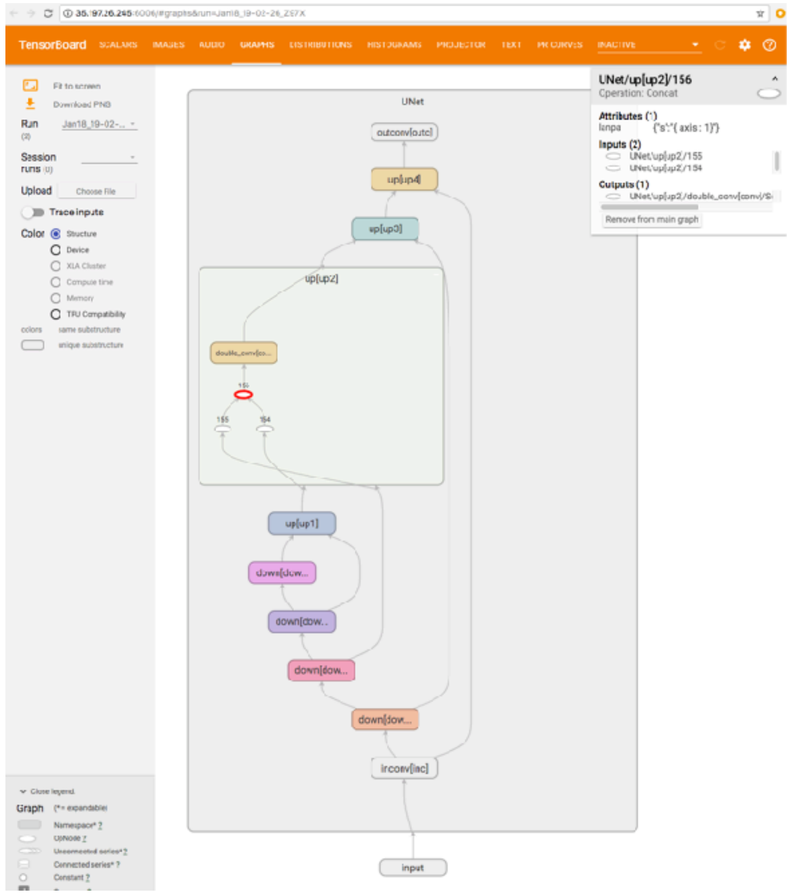
Distributed PyTorch

- MPI style distributed communication
- Broadcast Tensors to other nodes
- Reduce Tensors among nodes
  - for example: sum gradients among all nodes

Visualization

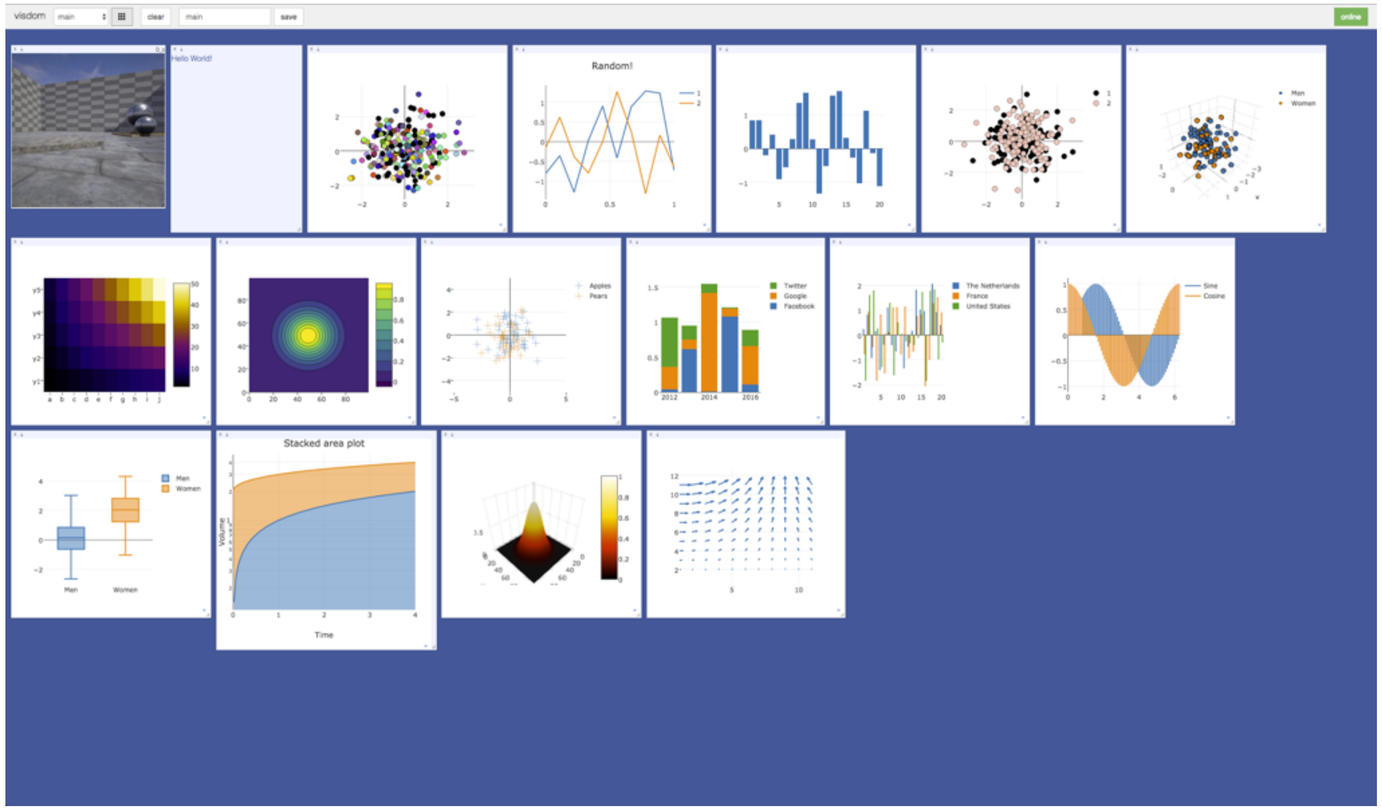
TensorBoard-PyTorch

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



Visdom

https://github.com/facebookresearch/visdom



Ecosystem

- Use the entire Python ecosystem at your will

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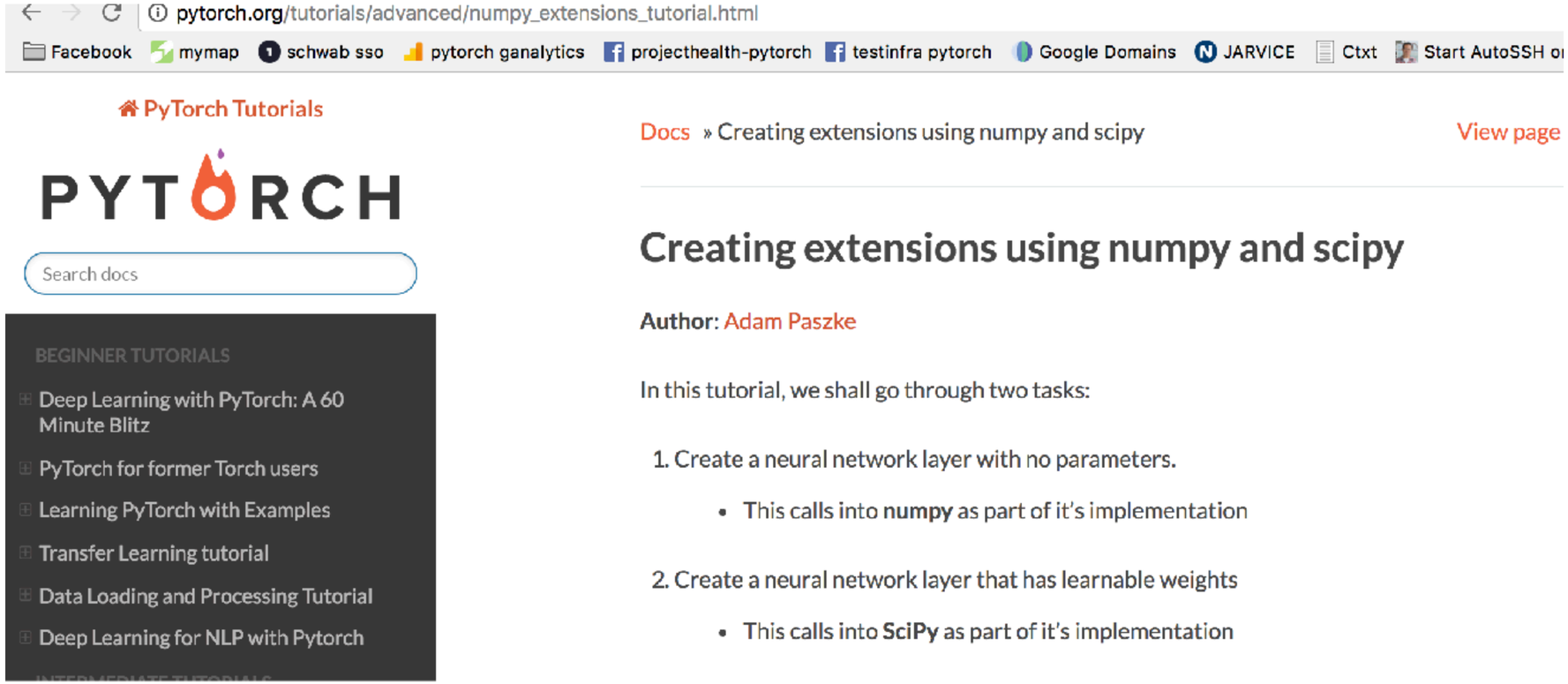


Ecosystem

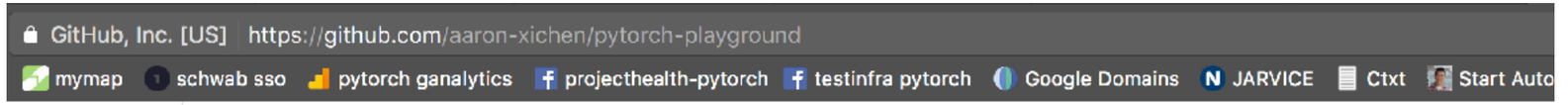
- A shared model-zoo:

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

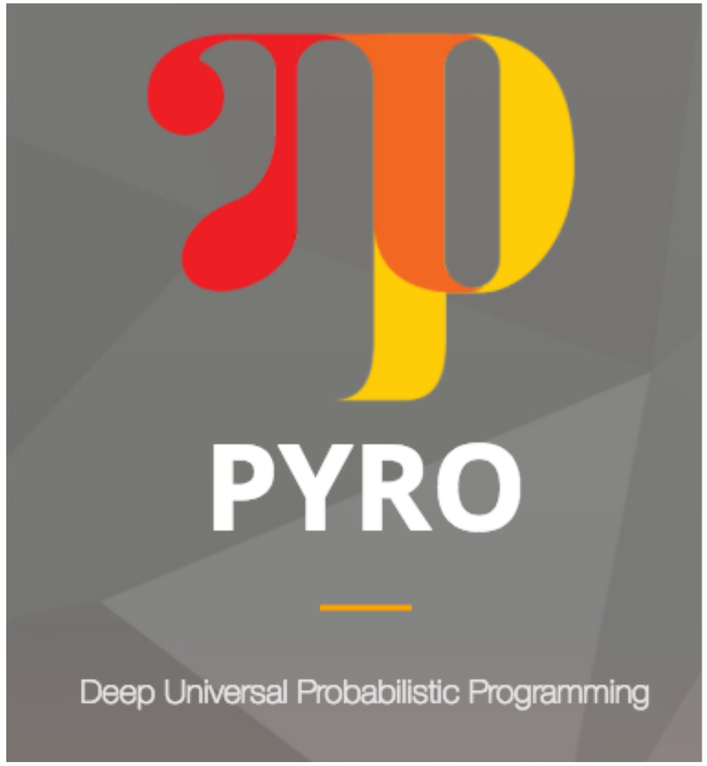


We evaluate the performance of popular dataset and models with linear quantized method. The bit-width of running mean and running variance in BN are 10 bits for all results. (except for 32-float)

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

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:

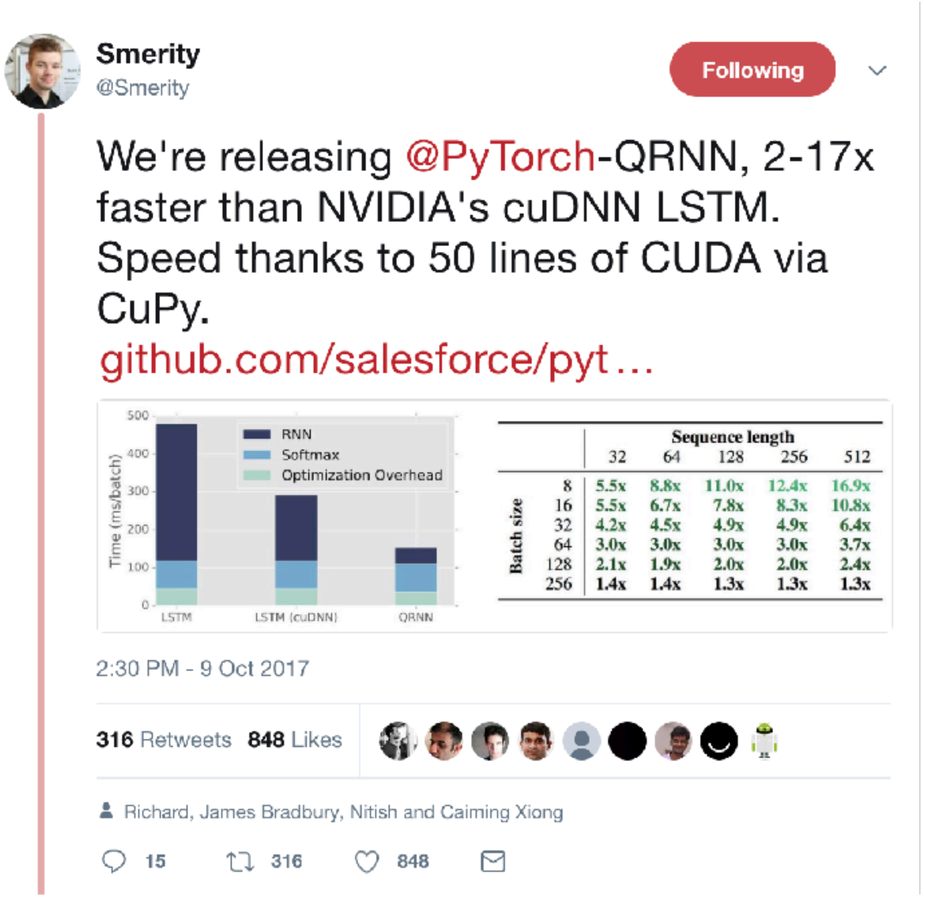
- Simple GP regression (example here)
- Simple GP classification (example here)
- Multitask GP regression (example here)
- Scalable GP regression using kernel interpolation (example here)
- Scalable GP classification using kernel interpolation (example here)
- Deep kernel learning (example here)
- And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

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

Ecosystem

- QRNN - 2x to 17x faster than LSTM

https://github.com/salesforce/pytorch-qrnn



Ecosystem

- CycleGAN, pix2pix

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

Ecosystem

- Machine Translation

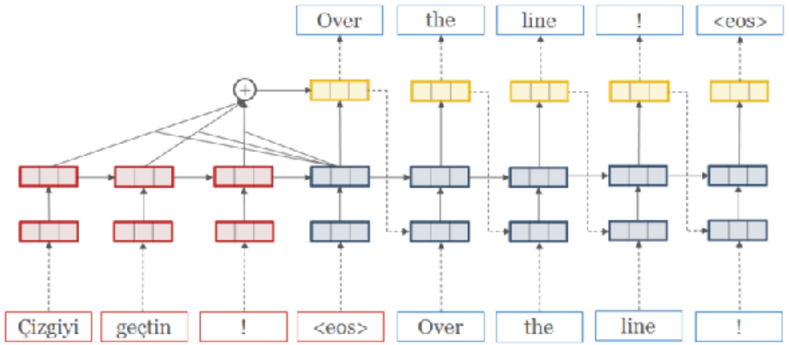
OpenNMT-py: Open-Source Neural Machine Translation

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.

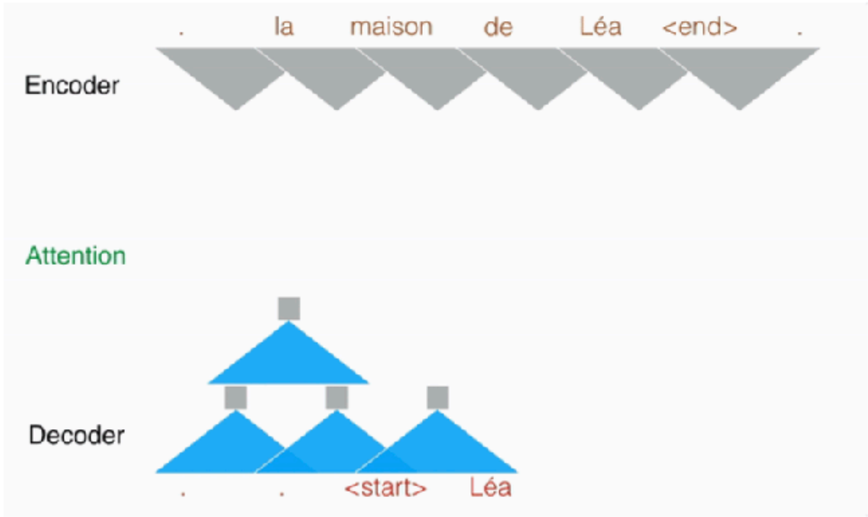
OpenNMT-py is run as a collaborative open-source project. It is maintained by Sasha Rush (Cambridge, MA), Ben Peters (Saarbrücken), and Jianyu Zhan (Shenzhen). The original code was written by Adam Lerer (NYC). We love contributions. Please consult the Issues page for any Contributions Welcome tagged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



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

FAIR Sequence-to-Sequence Toolkit (PyTorch)

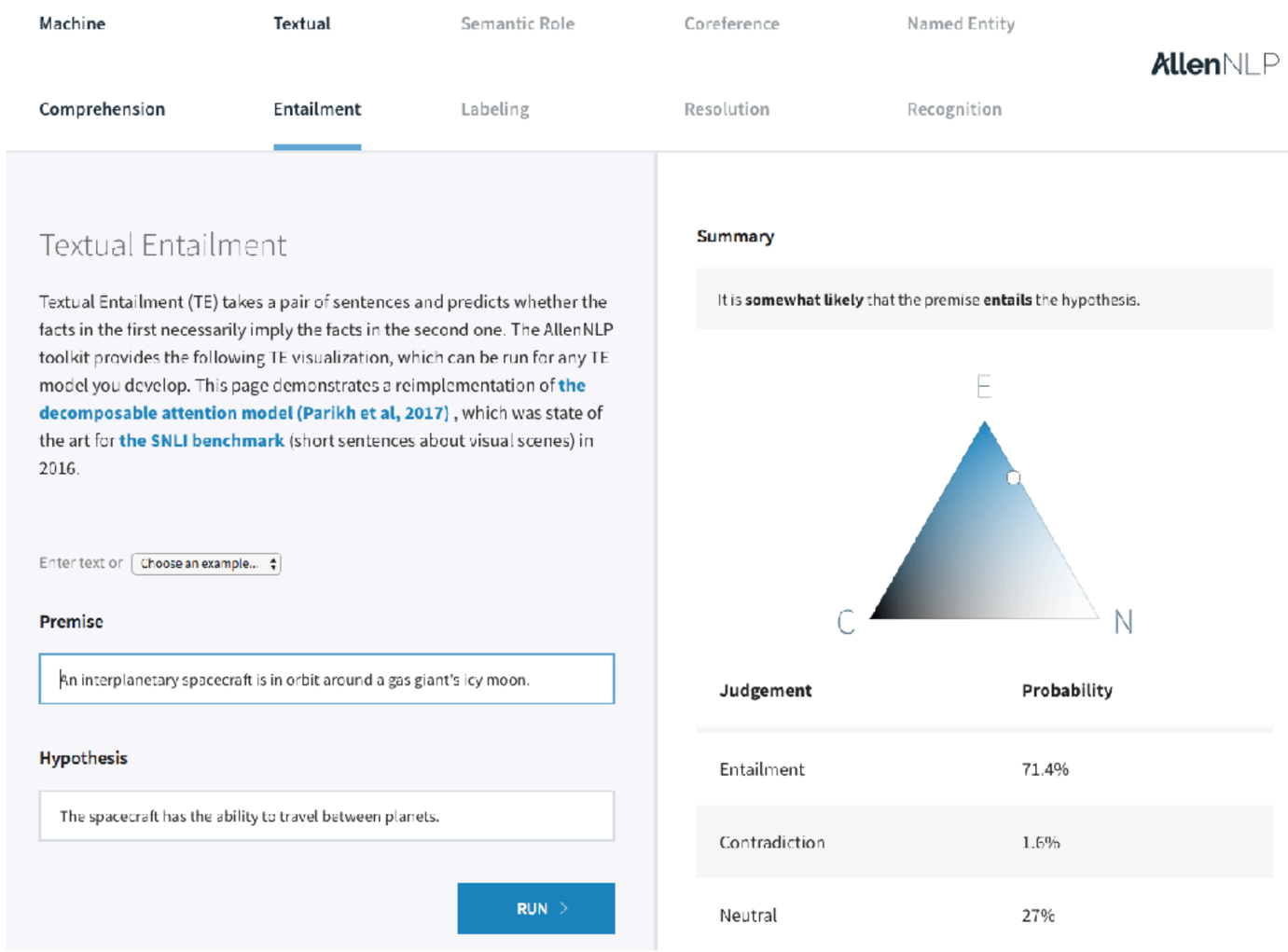
This is a PyTorch version of fairseq, a sequence-to-sequence learning toolkit from Facebook AI Research. The original authors of this reimplementation are (in no particular order) Sergey Edunov, Myle Ott, and Sam Gross. The toolkit implements the fully convolutional model described in Convolutional Sequence 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/

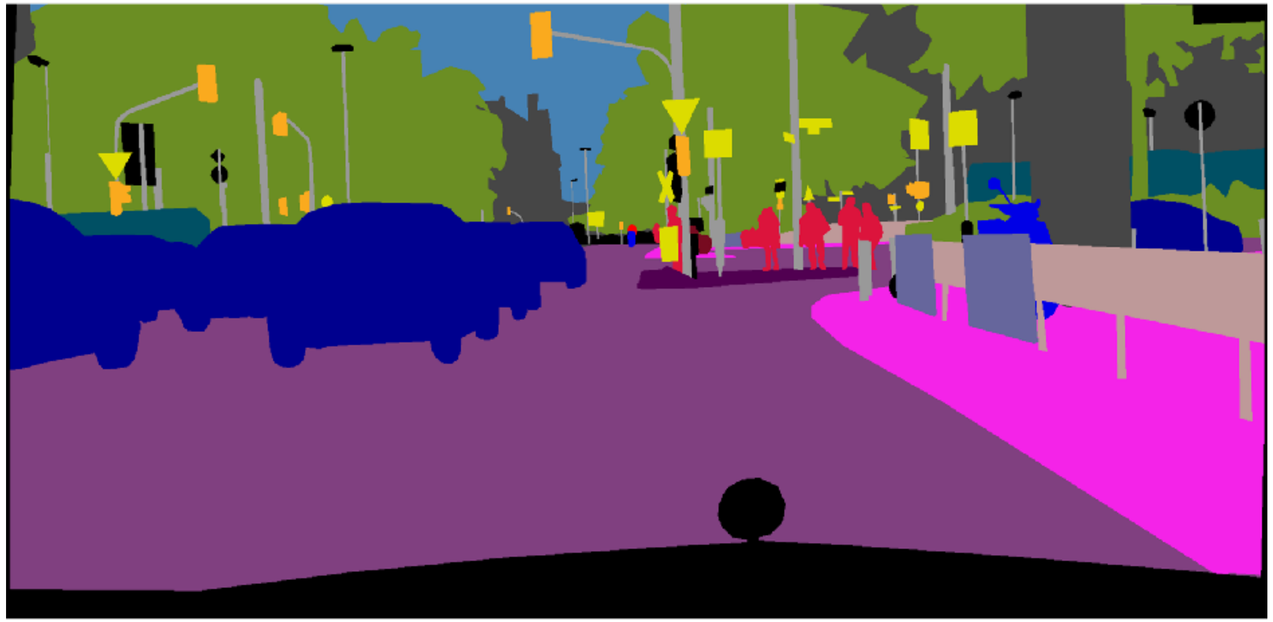


Ecosystem

- Pix2PixHD

https://github.com/NVIDIA/pix2pixHD

Input labels

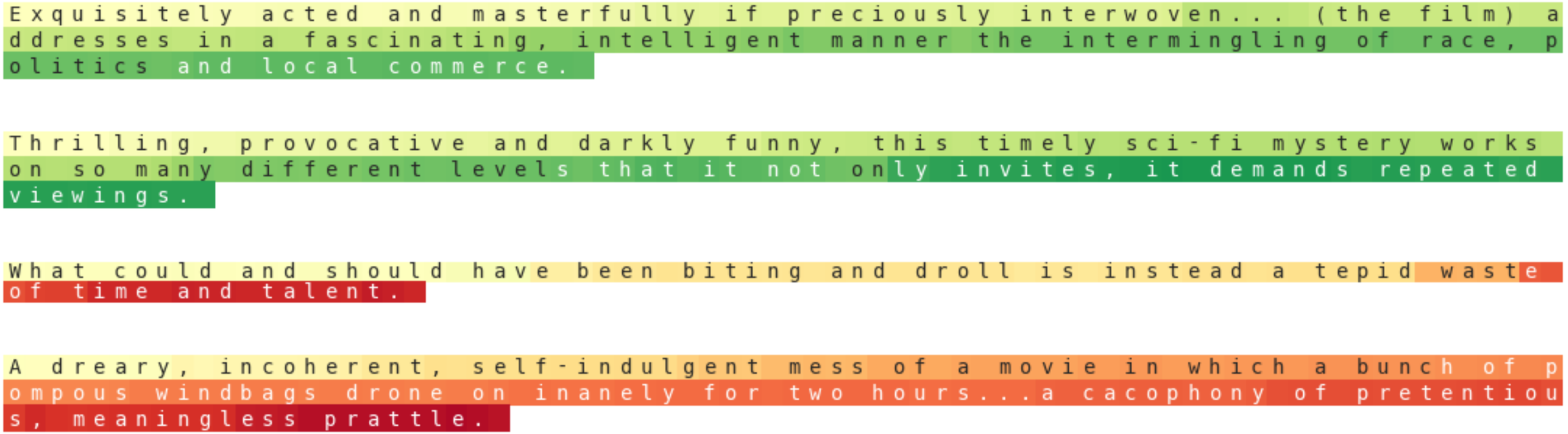


Synthesized image

Ecosystem

- Sentiment Discovery

https://github.com/NVIDIA/sentiment-discovery



Ecosystem

- FlowNet2: Optical Flow Estimation with Deep Networks

https://github.com/NVIDIA/flownet2-pytorch

With ❤ from

http://pytorch.org

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