Frameworks

Computational Linguistics: Jordan Boyd-Graber
University of Maryland
NEURAL NETWORKS IN PYTORCH

Slides adapted from Soumith Chintala

Data and Model (should be familiar)

Data

x_1	x_2	y
1.00	1.00	0.00
1.00	0.00	1.00
0.00	0.00	0.00
0.00	1.00	1.00

First Layer

$$w^{(1)} = \begin{bmatrix} 1.00 & 1.00 \\ 1.00 & 1.00 \end{bmatrix} \tag{1}$$

$$b^{(1)} = \begin{bmatrix} 0.00 & 1.00 \end{bmatrix} \tag{2}$$

Second Layer

$$w^{(2)} = \begin{bmatrix} 0.00 & 0.00 \end{bmatrix} \tag{3}$$

$$b^{(2)} = 0.00 \tag{4}$$

Using ReLU as non-linearity

ReLu Model

ReLu Model

```
class ReLuModel(nn.Module):
    def __init__(self, input_size=2, hidden_dim=2, num_clas
        super(ReLuModel, self).__init__()
        self.first_layer = nn.Linear(input_size, hidden_dim
        self.second_layer = nn.Linear(hidden_dim, num_class

    def forward(self, x):
        first_layer = self.first_layer(x)
        first_activation = first_layer.clamp(min=0)
        second_layer = self.second_layer(first_activation)
        out = second_layer.clamp(min=0)
        return out
```

Learning

Learning

```
loss_func = nn.MSELoss()
optimizer = torch.optim.SGD(relu.parameters(), lr=0.1)
for ii in range(kITER):
    for x, y in zip(data_x, data_y):
        optimizer.zero_grad()
        loss = loss_func(relu.forward(x), y)
        loss.backward()
        optimizer.step()
```

Inspecting Model

```
def model_string(self):
    first_layer = "%0.2f %0.2f\n%0.2f %0.2f\n" % \
                  (self.first_layer.weight.data[0][0],
                   self.first_layer.weight.data[0][1],
                   self.first_layer.weight.data[1][0],
                   self.first_layer.weight.data[0][1])

    first_bias = "%0.2f %0.2f\n" % \
                 (self.first_layer.bias.data[0],
                  self.first_layer.bias.data[1])

    second_layer = "%0.2f %0.2f\n" % \
                   (self.second_layer.weight.data[0][0]
                    self.second_layer.weight.data[0][1]

    second_bias = "%0.2f" % self.second_layer.bias.data

    return "FL: " + first_layer + "FB: " + first_bias +
```

Inspecting Model

```
FL: 1.00 1.00
1.00 1.00
FB: 0.00 1.00
SL: 0.00 0.00
SB: 0.00
```

Running Computation Forward

```
>>> x = torch.Tensor(1, 5)
>>> x
tensor([[ 0.0000, -0.0000,  0.0000, -0.0000,  0.0000]])
>>> x = x*0 + 1
>>> x
tensor([[1., 1., 1., 1., 1.]])
>>> model.forward(x)
tensor([[-0.2263,  0.5485]], grad_fn=<ThAddmmBackward>)
```

Models and Parameters

- **Parameters** are the things that we optimize over (vectors, matrices).
- **Model** is a collection of parameters.
- **Parameters** out-live the computation graph.

Modules allow computation graph

- Each module must implement forward function
- If forward function just uses built-in modules, autograd works
- If not, you'll need to implement backward function (i.e., backprop)

Modules allow computation graph

- Each module must implement forward function
- If forward function just uses built-in modules, autograd works
- If not, you'll need to implement backward function (i.e., backprop)
  - input: as many Tensors as outputs of module (gradient w.r.t. that output)
  - output: as many Tensors as inputs of module (gradient w.r.t. its corresponding input)
  - If inputs do not need gradient (static) you can return None

Trainers and Backprop

- Initialize a Optimizer with a given model's parameter
- Get output for an example / minibatch
- Compute loss and backpropagate
- Take step of Optimizer
- Repeat . . .

Trainers and Backprop

```
model = dy.Model()
optimizer = torch.optim.SGD(model.parameters(), lr=learning

# Training the Model
for epoch in range(num_epochs):
    for i, (Variable(doc), Variable(label)) in enumerate(tr
        optimizer.zero_grad()
        outputs = model(doc)
        loss = nn.CrossEntropyLoss(doc, label)
        loss.backward()
        optimizer.step()
```

Options for Optimizers

```
Adadelta
Adagrad
Adam
LBFGS
SGD
```

Closure (LBFGS), learning rate, etc.

Multilayer Perceptron for XOR

- Model

$$\hat{y} = \sigma(\hat{v} \cdot \tanh(U\vec{x} + b)) \tag{5}$$

- Loss

$$\ell = \begin{cases} -\log \hat{y} & \text{if } y = 0 \\ -\log(1 - \hat{y}) & \text{if } y = 1 \end{cases} \tag{6}$$

Imports and Data

```
import dynet as dy
import random

data =[ ([0,1],0),
        ([1,0],0),
        ([0,0],1),
        ([1,1],1) ]
```

Create Model

```
model = dy.Model()
pU = model.add_parameters((4,2))
pb = model.add_parameters(4)
pv = model.add_parameters(4)

trainer = dy.SimpleSGDTrainer(model)
closs = 0.0
```

```
for x,y in data:
    # create graph for computing loss
    dy.renew_cg()
    U = dy.parameter(pU)
    b = dy.parameter(pb)
    v = dy.parameter(pv)
    x = dy.inputVector(x)
    # predict
    yhat = dy.logistic(dy.dot_product(v,dy.tanh(U*x+b)))
    # loss
    if y == 0:
        loss = -dy.log(1 - yhat)
    elif y == 1:
        loss = -dy.log(yhat)

    closs += loss.scalar_value() # forward
    loss.backward()
    trainer.update()
```

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```

Important: loss expression defines objective you're optimizing

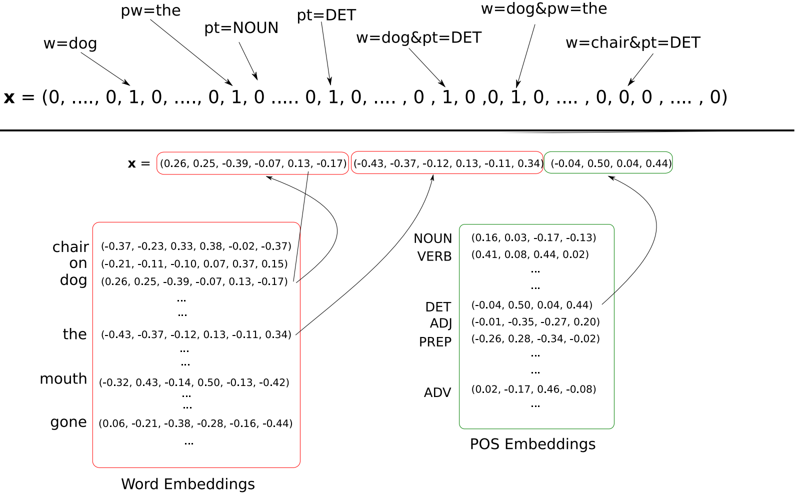
Key Points

- Create computation graph for each example.
- Graph is built by composing expressions.
- Functions that take expressions and return expressions define graph components.

Word Embeddings and Lookup Parameters

- In NLP, it is very common to use feature embeddings
- Each feature is represented as a d-dim vector
- These are then summed or concatenated to form an input vector
- The embeddings can be pre-trained
- But they are usually trained (fine-tunded) with the model

"feature embeddings"



```
import torch
import torch.nn as nn
import torch.nn.functional as F
import torch.optim as optim

torch.manual_seed(1)
word_to_ix = {"hello": 0, "world": 1}
embeds = nn.Embedding(2, 5)  # 2 words in vocab, 5 dimensio
lookup_tensor = torch.tensor([word_to_ix["hello"]], dtype=t
hello_embed = embeds(lookup_tensor)
```

Deep Unordered Composition Rivals Syntactic Methods for Text Classification

Mohit Iyyer,[1] **Varun Manjunatha,**[1] **Jordan Boyd-Graber,**[2] **Hal Daumé III**[1]
[1]University of Maryland, Department of Computer Science and UMIACS
[2]University of Colorado, Department of Computer Science
{miyyer,varunm,hal}@umiacs.umd.edu, Jordan.Boyd.Graber@colorado.edu

Implementing a non-trivial example ...

Deep Averaging Network

$$
\begin{aligned}
&w_1, \dots, w_N \\
&\quad\downarrow \\
z_0 &= \text{CBOW}(w_1, \dots, w_N) \\
z_1 &= g(W_1 z_0 + b_1) \\
z_2 &= g(W_2 z_1 + b_2) \\
\hat{y} &= \text{softmax}(z_2)
\end{aligned}
$$

- Works about as well as more complicated models
- Strong baseline
- Key idea: Continuous Bag of Words

$$\text{CBOW}(w_1, \dots, w_N) = \sum_i E[w_i] \tag{7}$$

- Actual non-linearity doesn't matter, we'll use tanh
- Let's implement in DyNet

Deep Averaging Network

$w_1, \dots, w_N$

$\downarrow$

$z_0 = \text{CBOW}(w_1, \dots, w_N)$

$z_1 = g(z_1)$

$z_2 = g(z_2)$

$\hat{y} = \text{softmax}(z_3)$

Encode the document

```
def encode_doc(doc):
    doc = [w2i[w] for w in doc]
    embs = [E[idx] for idx in doc]
    return dy.esum(embs)
```

First Layer

```
def layer1(x):
    W = dy.parameter(pW1)
    b = dy.parameter(pb1)
    return dy.tanh(W*x+b)
```

Second Layer

```
def layer2(x):
    W = dy.parameter(pW2)
    b = dy.parameter(pb2)
    return dy.tanh(W*x+b)
```

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Loss

```
def do_loss(probs, label):
    label = label_indicator[label]
    return -dy.log(dy.pick(probs,label)) # select that index
```

Putting it all together

```
def predict_labels(doc):
    x = encode_doc(doc)
    h = layer1(x)
    y = layer2(h)
    return dy.softmax(y)
```

Training

```
for (doc, label) in data:
    dy.renew_cg()
    probs = predict_labels(doc)

    loss = do_loss(probs,label)
    loss.forward()
    loss.backward()
    trainer.update()
```

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Summary

- Computation Graph
- Expressions ($\approx$ nodes in the graph)
- Parameters, LookupParameters
- Model (a collection of parameters)
- Trainers
- Create a graph for each example, compute loss, backdrop, update