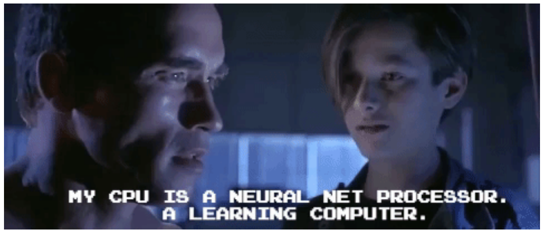
CS378: Natural Language Processing

Lecture 6: NN Implementation



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Announcements

- Assignment 1 due today
- Assignment 2 out today, due in two weeks
- Fairness response due Tuesday (submit on Canvas)
- Slip days: do not need to notify me
- A1 learning rate / initialization / objective / etc.

Recap

Classification Review

- See Instapoll

Neural Networks

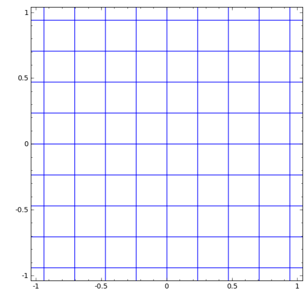
Neural Networks

$$\mathbf{z} = g(V f(\mathbf{x}) + \mathbf{b})$$

Nonlinear transformation — Warp space — Shift

$$y_{\text{pred}} = \text{argmax}_y \mathbf{w}_y^\top \mathbf{z}$$

- Ignore shift / +**b** term for the rest of the course



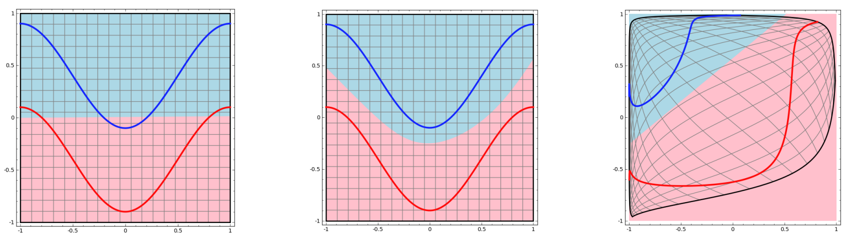
Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Neural Networks

Linear classifier

Neural network

Linear classification in the transformed space!



Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

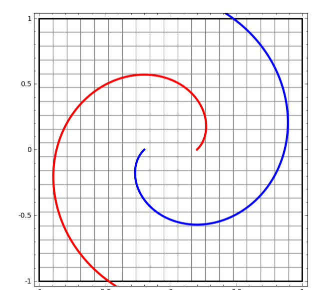
Deep Neural Networks

$$\mathbf{z}_1 = g(V_1 f(\mathbf{x}))$$

$$\mathbf{z}_2 = g(V_2 \mathbf{z}_1)$$

$$\dots$$

$$y_{\text{pred}} = \text{argmax}_y \mathbf{w}_y^\top \mathbf{z}_n$$



Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Feedforward Networks

Vectorization and Softmax

$$P(y|\mathbf{x}) = \frac{\exp(\mathbf{w}_y^\top f(\mathbf{x}))}{\sum_{y' \in \mathcal{Y}} \exp(\mathbf{w}_{y'}^\top f(\mathbf{x}))}$$

- Single scalar probability
- Three classes, "different weights"

			softmax		
$\mathbf{w}_1^\top f(\mathbf{x})$		-1.1		0.036	
$\mathbf{w}_2^\top f(\mathbf{x})$	=	2.1	$\longrightarrow$	0.89	class probs
$\mathbf{w}_3^\top f(\mathbf{x})$		-0.4		0.07	

- Softmax operation = "exponentiate and normalize"
- We write this as: $\mathrm{softmax}(Wf(\mathbf{x}))$

Logistic Regression as a Neural Net

$$P(y|\mathbf{x}) = \frac{\exp(\mathbf{w}_y^\top f(\mathbf{x}))}{\sum_{y' \in \mathcal{Y}} \exp(\mathbf{w}_{y'}^\top f(\mathbf{x}))}$$

- Single scalar probability

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wf(\mathbf{x}))$$

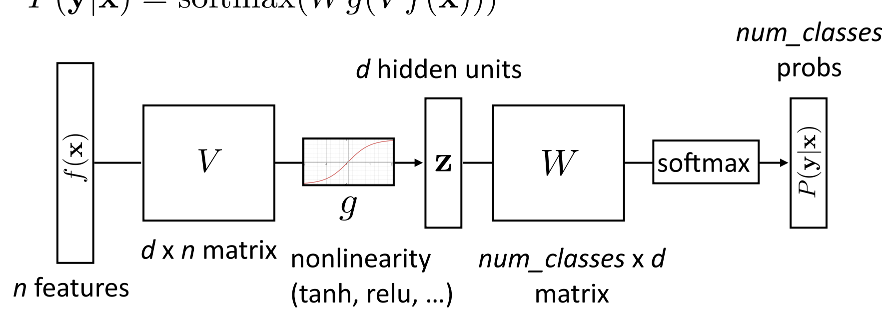
- Weight vector per class; *W* is [num classes x num feats]

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$$

- Now one hidden layer

Neural Networks for Classification

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$$



Backpropagation
(with pictures! Full derivations at the end of the slides)

Training Objective

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

- Consider the log likelihood of a single training example:

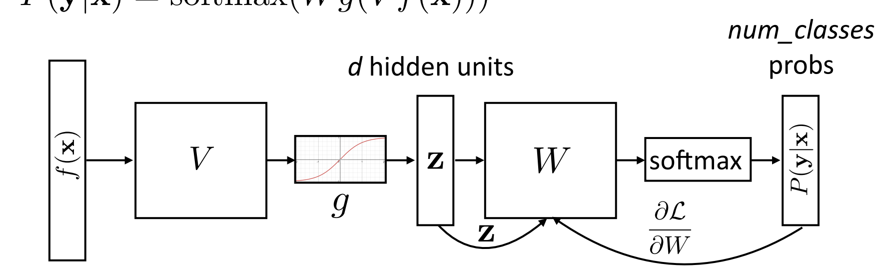
$$\mathcal{L}(\mathbf{x}, i^*) = \log P(y = i^*|\mathbf{x})$$

where *i** is the index of the gold label for an example

- Backpropagation is an algorithm for computing gradients of *W* and *V* (and in general any network parameters)

Backpropagation: Picture

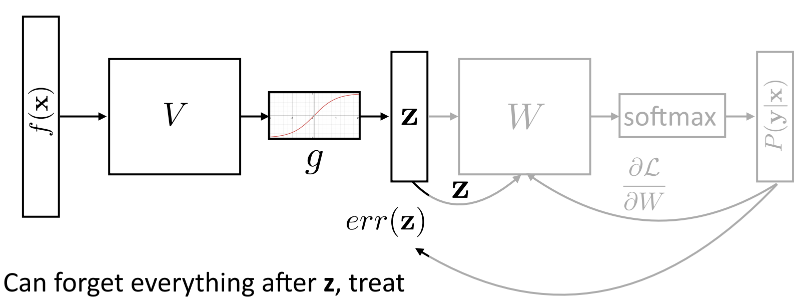
$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



- Gradient w.r.t. *W*: looks like logistic regression, can be computed treating **z** as the features

Backpropagation: Picture

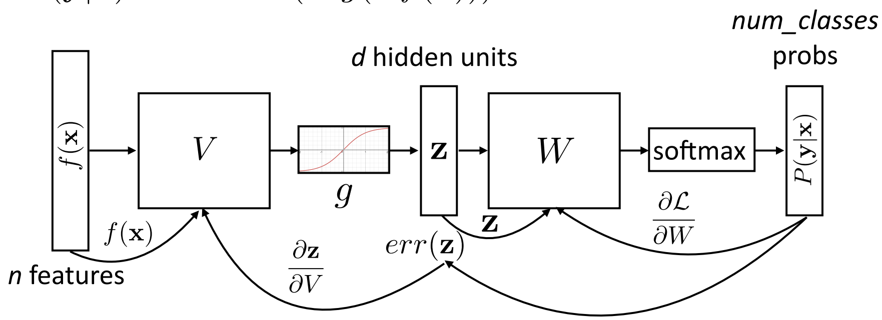
$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$



- Can forget everything after **z**, treat it as the output and keep backpropping

Backpropagation: Picture

$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(W g(V f(\mathbf{x})))$



- Combine backward gradients with forward-pass products

Pytorch Basics

(code examples are on the course website: ffnn_example.py)

PyTorch

- Framework for defining computations that provides easy access to derivatives
- Module: defines a neural network (can use wrap other modules which implement predefined layers)
- If forward() uses crazy stuff, you have to write backward yourself

```
torch.nn.Module

  # Takes an example x and computes result
  forward(x):
    ...
  # Computes gradient after forward() is called
  backward(): # produced automatically
    ...
```

Computation Graphs in Pytorch

- Define forward pass for $P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(W g(V f(\mathbf{x})))$

```
class FFNN(nn.Module):
    def __init__(self, input_size, hidden_size, out_size):
        super(FFNN, self).__init__()
        self.V = nn.Linear(input_size, hidden_size)
        self.g = nn.Tanh() # or nn.ReLU(), sigmoid()...
        self.W = nn.Linear(hidden_size, out_size)
        self.softmax = nn.Softmax(dim=0)

    def forward(self, x):
        return self.softmax(self.W(self.g(self.V(x))))
```

(syntactic sugar for forward)

Input to Network

- Whatever you define with torch.nn needs its input as some sort of tensor, whether it's integer word indices or real-valued vectors

```
def form_input(x) -> torch.Tensor:
  # Index words/embed words/etc.
  return torch.from_numpy(x).float()
```

- torch.Tensor is a different datastructure from a numpy array, but you can translate back and forth fairly easily
- Note that **translating out of PyTorch will break backpropagation**; don't do this inside your Module

Training and Optimization

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

```
ffnn = FFNN(inp, hid, out)
optimizer = optim.Adam(ffnn.parameters(), lr=lr)
for epoch in range(0, num_epochs):
    for (input, gold_label) in training_data:
      ffnn.zero_grad() # clear gradient variables
      probs = ffnn.forward(input)
      loss = torch.neg(torch.log(probs)).dot(gold_label)
      loss.backward()
      optimizer.step()
```

one-hot vector of the label (e.g., [0, 1, 0])

negative log-likelihood of correct answer (can also use NLLLoss)

Initialization in Pytorch

```
class FFNN(nn.Module):
    def __init__(self, inp, hid, out):
        super(FFNN, self).__init__()
        self.V = nn.Linear(inp, hid)
        self.g = nn.Tanh()
        self.W = nn.Linear(hid, out)
        self.softmax = nn.Softmax(dim=0)
        nn.init.uniform(self.V.weight)
```

- Initializing to a nonzero value is critical. See optimization video on course website. (Pytorch does this by default so you don't necessarily have to include it.)

Training a Model

Define modules, etc.

Initialize weights and optimizer

For each epoch:

  For each batch of data:

    Zero out gradient

    Compute loss on batch

    Autograd to compute gradients and take step on optimizer

  [Optional: check performance on dev set to identify overfitting]

Run on dev/test set

Pytorch example

Batching

Batching

- Modify the training loop to run over multiple examples at once

```
# input is [batch_size, num_feats]
# gold_label is [batch_size, num_classes]
def make_update(input, gold_label)
    ...
    probs = ffnn.forward(input) # [batch_size, num_classes]
    loss = torch.sum(torch.neg(torch.log(probs)).dot(gold_label))
    ...
```

- Batch sizes from 1-100 often work well
- Can use the same network as before **without modification**

DANs

Word Embeddings

- Currently we think of words as "one-hot" vectors

  the = [1, 0, 0, 0, 0, 0, …]

  good = [0, 0, 0, 1, 0, 0, …]

  great = [0, 0, 0, 0, 0, 1, …]

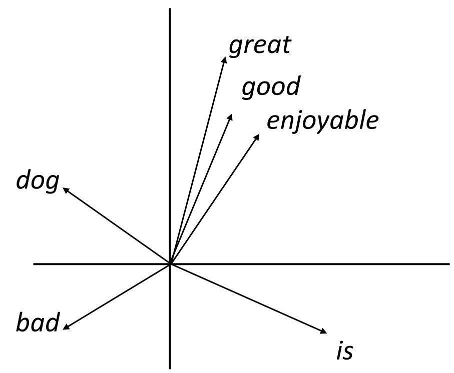
- *good* and *great* seem as dissimilar as *good* and *the*
- Neural networks are built to learn sophisticated nonlinear functions of continuous inputs; our inputs are weird and discrete

Word Embeddings

- Want a vector space where similar words have similar embeddings

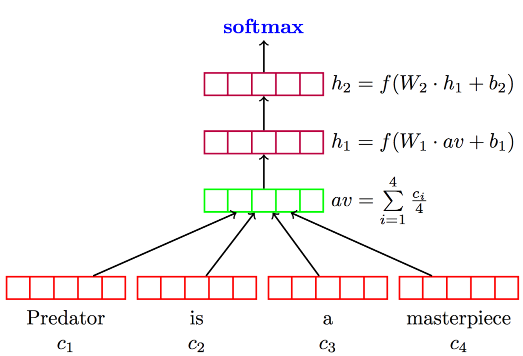
  great ≈ *good*

- Next lecture: come up with a way to produce these embeddings
- For each word, want "medium" dimensional vector (50-300 dims) representing it



Deep Averaging Networks

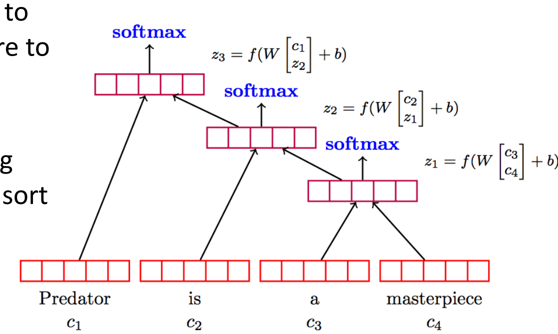
- Deep Averaging Networks: feedforward neural network on average of word embeddings from input



Iyyer et al. (2015)

Deep Averaging Networks

- Widely-held view: need to model syntactic structure to represent language
- Surprising that averaging can work as well as this sort of composition



Iyyer et al. (2015)

Sentiment Analysis

No pretrained embeddings → DAN-RAND

Model	RT	SST fine	SST bin	IMDB	Time (s)
DAN-ROOT	—	46.9	85.7	—	**31**
DAN-RAND	77.3	45.4	83.2	88.8	136
DAN	80.3	47.7	86.3	89.4	136
NBOW-RAND	76.2	42.3	81.4	88.9	91
NBOW	79.0	43.6	83.6	89.0	91
BiNB	—	41.9	83.1	—	—
NBSVM-bi	79.4	—	—	91.2	—
RecNN*	77.7	43.2	82.4	—	—
RecNTN*	—	45.7	85.4	—	—
DRecNN	—	49.8	86.6	—	431
TreeLSTM	—	**50.6**	86.9	—	—
DCNN*	—	48.5	86.9	89.4	—
PVEC*	—	48.7	87.8	**92.6**	—
CNN-MC	**81.1**	47.4	**88.1**	—	2,452
WRRBM*	—	—	—	89.2	—

Bag-of-words: NBOW-RAND, NBOW, BiNB, NBSVM-bi

Tree-structured neural networks: RecNN*, RecNTN*, DRecNN, TreeLSTM, DCNN*, PVEC*, CNN-MC, WRRBM*

Iyyer et al. (2015) (DAN)

Wang and Manning (2012) (NBSVM-bi)

Kim (2014) (CNN-MC)

Deep Averaging Networks

Sentence	DAN	DRecNN	Ground Truth
who knows what exactly godard is on about in this film, but his words and images do n't have to add up to mesmerize you.	positive	positive	positive
it's so good that its relentless, polished wit can withstand not only inept school productions, but even oliver parker's movie adaptation	negative	positive	positive
too bad, but thanks to some lovely comedic moments and several fine performances, it's not a total loss	negative	negative	positive
this movie was not good	negative	negative	negative
this movie was good	positive	positive	positive
this movie was bad	negative	negative	negative
the movie was not bad	negative	negative	positive

- Will return to compositionality with syntax and LSTMs

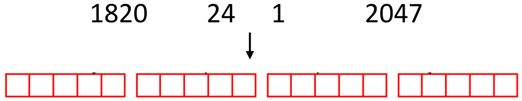
Iyyer et al. (2015)

Word Embeddings in PyTorch

- torch.nn.Embedding: maps vector of indices to matrix of word vectors

Predator is a masterpiece

1820 24 1 2047



- *n* indices => *n* x *d* matrix of *d*-dimensional word embeddings
- *b* x *n* indices => *b* x *n* x *d* tensor of *d*-dimensional word embeddings

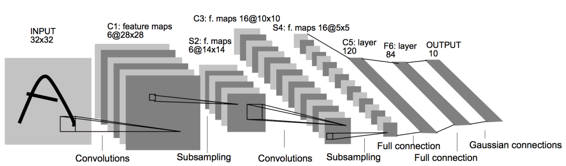
Word Embeddings

Word Embeddings

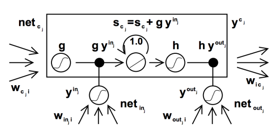
Neural Nets History

History: NN "dark ages"

- Convnets: applied to MNIST by LeCun in 1998



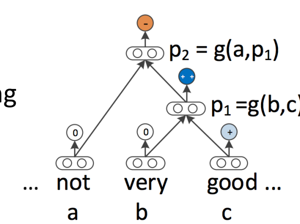
- LSTMs: Hochreiter and Schmidhuber (1997)



- Henderson (2003): neural shift-reduce parser, not SOTA

2008-2013: A glimmer of light…

- Collobert and Weston 2011: "NLP (almost) from scratch"
  - Feedforward neural nets induce features for sequential CRFs ("neural CRF")
- Krizhevskey et al. (2012): AlexNet for vision
- Socher 2011-2014: tree-structured RNNs working okay



2014: Stuff starts working

- Kim (2014) + Kalchbrenner et al. (2014): sentence classification / sentiment (convnets work for NLP?)
- Sutskever et al. (2014) + Bahdanau et al. (2014): seq2seq for neural MT (LSTMs work for NLP?)
- Chen and Manning transition-based dependency parser (feedforward)
- 2015: explosion of neural nets for everything under the sun

Why didn't they work before?

- **Datasets too small**: for MT, not really better until you have 1M+ parallel sentences (and really need a lot more)
- **Optimization not well understood**: good initialization, per-feature scaling + momentum (Adagrad / Adadelta / Adam) work best out-of-the-box
  - **Regularization**: dropout is pretty helpful
  - **Computers not big enough**: can't run for enough iterations
- **Inputs**: need word representations to have the right continuous semantics

Backpropagation — Derivations (not covered in lecture, optional)

Training Neural Networks

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(W\mathbf{z}) \qquad \mathbf{z} = g(Vf(\mathbf{x}))$$

- Maximize log likelihood of training data

$$\mathcal{L}(\mathbf{x}, i^*) = \log P(y = i^*|\mathbf{x}) = \log\left(\text{softmax}(W\mathbf{z}) \cdot e_{i^*}\right)$$

- i^*: index of the gold label
- e_i: 1 in the ith row, zero elsewhere. Dot by this = select ith index

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

Computing Gradients

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

- Gradient with respect to *W:*

$$\frac{\partial}{\partial W_{ij}} \mathcal{L}(\mathbf{x}, i^*) = \begin{cases} \mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j & \text{if } i = i^* \\ -P(y = i|\mathbf{x})\mathbf{z}_j & \text{otherwise} \end{cases}$$

gradient w.r.t. *W*

j

i

$\mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j$

$-P(y = i|\mathbf{x})\mathbf{z}_j$

- Looks like logistic regression with ***z*** as the features!

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

$\mathbf{z} = g(Vf(\mathbf{x}))$ Activations at hidden layer

- Gradient with respect to *V*: apply the chain rule

$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial V_{ij}}$$

[some math…]

$err(\text{root}) = e_{i^*} - P(\mathbf{y}|\mathbf{x})$
dim = *num_classes*

$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} = err(\mathbf{z}) = W^\top err(\text{root})$
dim = *d*

Computing Gradients: Backpropagation

$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

$\mathbf{z} = g(Vf(\mathbf{x}))$ Activations at hidden layer

- Gradient with respect to *V*: apply the chain rule

$$\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial V_{ij}} = \frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} \frac{\partial \mathbf{z}}{\partial V_{ij}} \qquad \frac{\partial \mathbf{z}}{\partial V_{ij}} = \frac{\partial g(\mathbf{a})}{\partial \mathbf{a}} \frac{\partial \mathbf{a}}{\partial V_{ij}} \qquad \mathbf{a} = Vf(\mathbf{x})$$

- First term: gradient of nonlinear activation function at ***a*** (depends on current value)
- Second term: gradient of linear function
- First term: *err*(**z**); represents gradient w.r.t. **z**

Backpropagation

$$P(\mathbf{y}|\mathbf{x}) = \text{softmax}(Wg(Vf(\mathbf{x})))$$

- Step 1: compute $err(\text{root}) = e_{i^*} - P(\mathbf{y}|\mathbf{x})$ (vector)
- Step 2: compute derivatives of *W* using *err*(root) (matrix)
- Step 3: compute $\frac{\partial \mathcal{L}(\mathbf{x}, i^*)}{\partial \mathbf{z}} = err(\mathbf{z}) = W^\top err(\text{root})$ (vector)
- Step 4: compute derivatives of *V* using *err*(**z**) (matrix)
- Step 5+: continue backpropagation if necessary