CS388: Natural Language Processing

Lecture 6: Neural Networks

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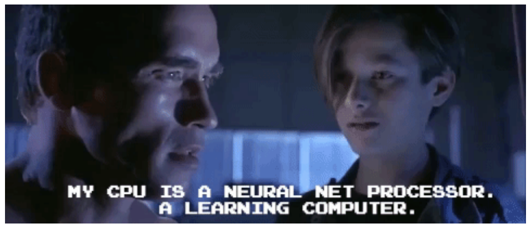
TEXAS

The University of Texas at Austin

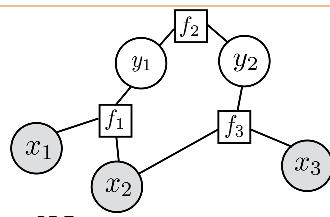


Administrivia

- Mini 1 graded later this week
- Project 1 due in a week

Recall: CRFs

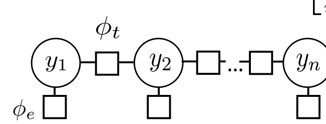
$$P(\mathbf{y}|\mathbf{x}) = \frac{1}{Z} \exp \left(\sum_{k=1}^{n} w^\top f_k(\mathbf{x}, \mathbf{y}) \right)$$



- Conditional model: x's are observed
- Naive Bayes : logistic regression :: HMMs : CRFs
  local vs. global normalization <-> generative vs. discriminative
  (locally normalized discriminative models do exist (MEMMs))
- HMMs: in the standard setup, emissions consider one word at a time
- CRFs: features over many words simultaneously, non-independent features (e.g., suffixes and prefixes), doesn't have to be a generative model

Recall: Sequential CRFs

- Model: $P(\mathbf{y}|\mathbf{x}) \propto \exp w^\top \left[\sum_{i=2}^{n} f_t(y_{i-1}, y_i) + \sum_{i=1}^{n} f_e(y_i, i, \mathbf{x}) \right]$



- Emission features capture word-level info, transitions enforce tag consistency
- Inference: argmax P(**y**|**x**) from Viterbi
- Learning: run forward-backward to compute posterior probabilities; then

$$\frac{\partial}{\partial w} \mathcal{L}(\mathbf{y}^*, \mathbf{x}) = \sum_{i=1}^{n} f_e(y_i^*, i, \mathbf{x}) - \sum_{i=1}^{n} \sum_{s} P(y_i = s|\mathbf{x}) f_e(s, i, \mathbf{x})$$

This Lecture

- Finish discussion of NER
- Beam search: in a few lectures
- Neural network history
- Neural network basics
- Feedforward neural networks + backpropagation
- Applications
- Implementing neural networks (if time)

NER

NER

- CRF with lexical features can get around 85 F1 on this problem
- Other pieces of information that many systems capture
- World knowledge:

The delegation met the president at the airport, Tanjug said.

Tanjug

From Wikipedia, the free encyclopedia

Tanjug (/ˈtʌnjʊɡ/) (Serbian Cyrillic: Тањуг) is a Serbian state news agency based in Belgrade.[2]

Nonlocal Features

The news agency Tanjug reported on the outcome of the meeting.

ORG?

PER?

The delegation met the president at the airport, Tanjug said.

- More complex factor graph structures can let you capture this, or just decode sentences in order and use features on previous sentences

Finkel and Manning (2008), Ratinov and Roth (2009)

Semi-Markov Models

Barack Obama will travel to Hangzhou today for the G20 meeting .

PER O LOC O ORG O

- Chunk-level prediction rather than token-level BIO
- ***y*** is a set of spans covering the sentence
- Pros: features can look at whole span at once
- Cons: there's an extra factor of n in the dynamic programs

Sarawagi and Cohen (2004)

Evaluating NER

B-PER I-PER O O O B-LOC O O O B-ORG O O

Barack Obama will travel to Hangzhou today for the G20 meeting .

PERSON LOC ORG

- Prediction of all Os still gets 66% accuracy on this example!
- What we really want to know: how many named entity *chunk* predictions did we get right?
  - Precision: of the ones we predicted, how many are right?
  - Recall: of the gold named entities, how many did we find?
  - F-measure: harmonic mean of these two

How well do NER systems do?

	System	Resources Used	F_1
+	LBJ-NER	Wikipedia, Nonlocal Features, Word-class Model	90.80
-	(Suzuki and Isozaki, 2008)	Semi-supervised on 1G-word unlabeled data	89.92
-	(Ando and Zhang, 2005)	Semi-supervised on 27M-word unlabeled data	89.31
-	(Kazama and Torisawa, 2007a)	Wikipedia	88.02
-	(Krishnan and Manning, 2006)	Non-local Features	87.24
-	(Kazama and Torisawa, 2007b)	Non-local Features	87.17
+	(Finkel et al., 2005)	Non-local Features	86.86

Ratinov and Roth (2009)

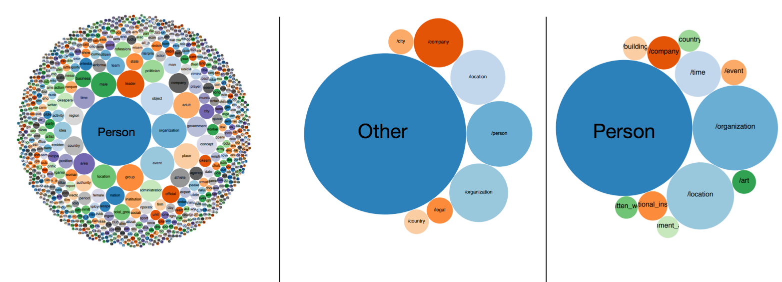
Lample et al. (2016)

LSTM-CRF (no char)	90.20
LSTM-CRF	**90.94**
S-LSTM (no char)	87.96
S-LSTM	90.33

BiLSTM-CRF + ELMo
Peters et al. (2018) **92.2**

BERT
Devlin et al. (2019) **92.8**

Modern Entity Typing



a) Our Dataset b) OntoNotes c) FIGER

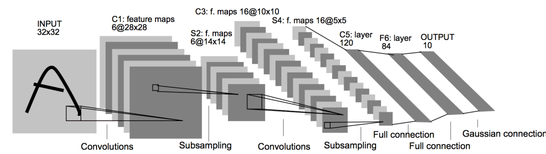
- More and more classes (17 -> 112 -> 10,000+)

Choi et al. (2018)

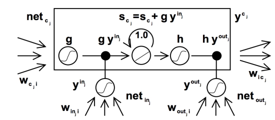
Neural Net History

History: NN "dark ages"

- Convnets: applied to MNIST by LeCun in 1998



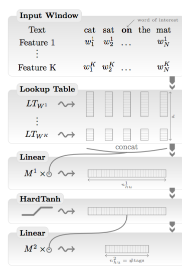
- LSTMs: Hochreiter and Schmidhuber (1997)



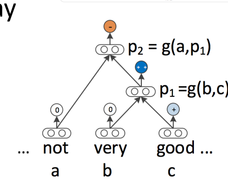
- Henderson (2003): neural shift-reduce parser, not SOTA

2008-2013: A glimmer of light…

- Collobert and Weston 2011: "NLP (almost) from scratch"
  - Feedforward neural nets induce features for sequential CRFs ("neural CRF")
  - 2008 version was marred by bad experiments, claimed SOTA but wasn't, 2011 version tied SOTA



- Socher 2011-2014: tree-structured RNNs working okay
- Krizhevskey et al. (2012): AlexNet for vision



2014: Stuff starts working

- Kim (2014) + Kalchbrenner et al. (2014): sentence classification / sentiment (convnets)
- Sutskever et al. + Bahdanau et al.: seq2seq for neural MT (LSTMs)
- Chen and Manning transition-based dependency parser (based on feedforward networks)
- 2015: explosion of neural nets for everything under the sun
- What made these work? **Data** (not as important as you might think), **optimization** (initialization, adaptive optimizers), **representation** (good word embeddings)

Neural Net Basics

Neural Networks

- Linear classification: $\text{argmax}_y w^\top f(x, y)$
- Want to learn intermediate conjunctive features of the input

*the movie was **not** all that **good***

I[contains *not* & contains *good*]

- How do we learn this if our feature vector is just the unigram indicators?

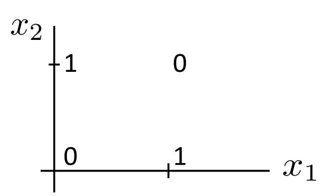
I[contains *not*], I[contains *good*]

Neural Networks: XOR

- Let's see how we can use neural nets to learn a simple nonlinear function
- Inputs $x_1, \ x_2$

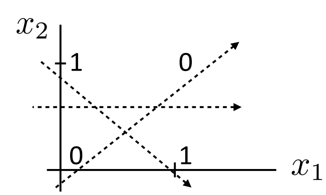
  $(\text{generally } \mathbf{x} = (x_1, \ldots, x_m))$
- Output y

  $(\text{generally } \mathbf{y} = (y_1, \ldots, y_n))$



x_1	x_2	$y = x_1 \text{ XOR } x_2$
0	0	0
0	1	1
1	0	1
1	1	0

Neural Networks: XOR



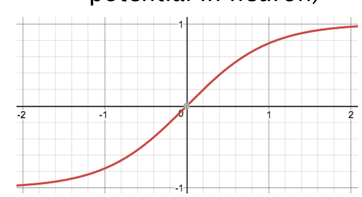
x_1	x_2	$x_1 \text{ XOR } x_2$
0	0	0
0	1	1
1	0	1
1	1	0

$y = a_1 x_1 + a_2 x_2$ X

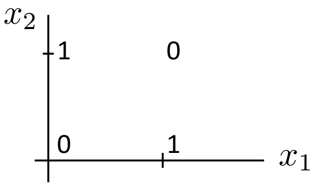
$y = a_1 x_1 + a_2 x_2 + a_3 \tanh(x_1 + x_2)$ ✓

"or"

(looks like action potential in neuron)



Neural Networks: XOR



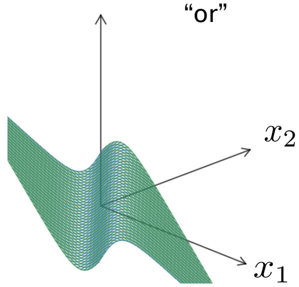
x_1	x_2	x_1 XOR x_2
0	0	0
0	1	1
1	0	1
1	1	0

$y = a_1 x_1 + a_2 x_2$ X

$y = a_1 x_1 + a_2 x_2 + a_3 \tanh(x_1 + x_2)$ ✔

$y = -x_1 - x_2 + 2\tanh(x_1 + x_2)$

"or"



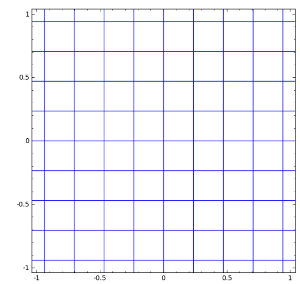
Neural Networks

Linear model: $y = \mathbf{w} \cdot \mathbf{x} + b$

$$y = g(\mathbf{w} \cdot \mathbf{x} + b)$$

$$\mathbf{y} = g(\mathbf{W}\mathbf{x} + \mathbf{b})$$

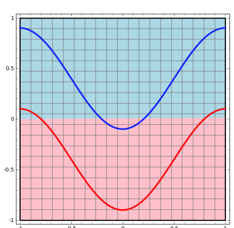
Nonlinear transformation   Warp space   Shift



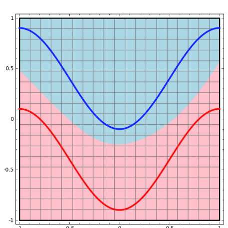
Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Neural Networks

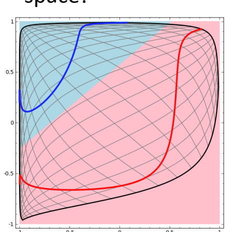
Linear classifier



Neural network



...possible because we transformed the space!



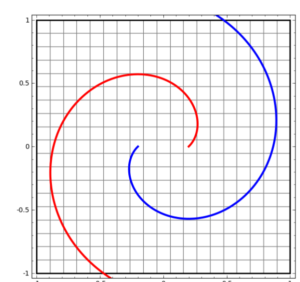
Taken from http://colah.github.io/posts/2014-03-NN-Manifolds-Topology/

Deep Neural Networks

$$\boldsymbol{y} = g(\boldsymbol{W}\boldsymbol{x} + \boldsymbol{b})$$

$$\mathbf{z} = g(\mathbf{V}\mathbf{y} + \mathbf{c})$$

$$\mathbf{z} = g(\mathbf{V}\underbrace{g(\mathbf{W}\mathbf{x} + \mathbf{b})}_{\text{output of first layer}} + \mathbf{c})$$



Check: what happens if no nonlinearity?

More powerful than basic linear models?

$$\mathbf{z} = \mathbf{V}(\mathbf{W}\mathbf{x} + \mathbf{b}) + \mathbf{c}$$

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

Feedforward Networks, Backpropagation

Logistic Regression with NNs

$$P(y|\mathbf{x}) = \frac{\exp(w^\top f(\mathbf{x}, y))}{\sum_{y'} \exp(w^\top f(\mathbf{x}, y'))}$$

- Single scalar probability

$$P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}\left([w^\top f(\mathbf{x}, y)]_{y \in \mathcal{Y}}\right)$$

- Compute scores for all possible labels at once (returns vector)

$$\mathrm{softmax}(p)_i = \frac{\exp(p_i)}{\sum_{i'} \exp(p_{i'})}$$

- softmax: exps and normalizes a given vector

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

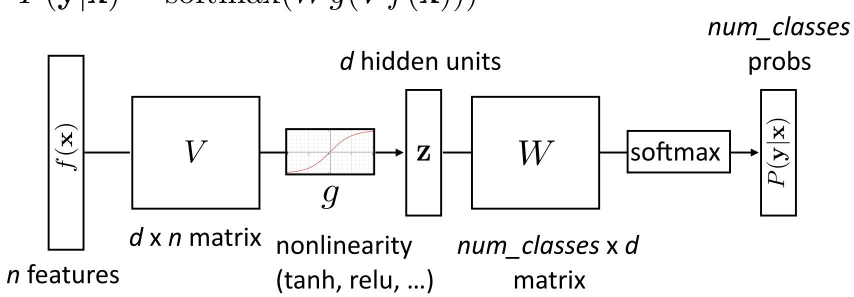
- Weight vector per class;
  W is [num classes x num feats]

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

- Now one hidden layer

Neural Networks for Classification

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



Training Neural Networks

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

- Maximize log likelihood of training data

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

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

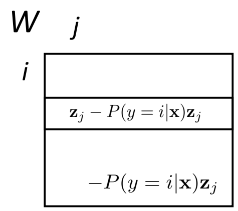
$$\mathcal{L}(\mathbf{x}, i^*) = W\mathbf{z} \cdot e_{i^*} - \log \sum_j \exp(W\mathbf{z}) \cdot e_j$$

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*

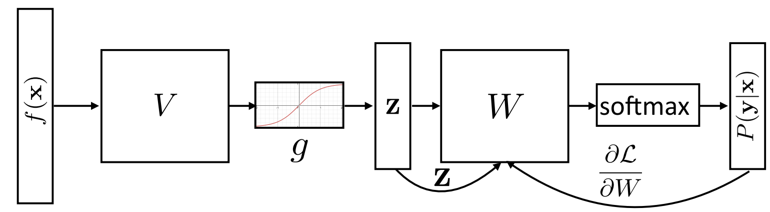
$$\frac{\partial}{\partial W_{ij}} \mathcal{L}(\mathbf{x}, i^*) = \begin{cases} \mathbf{z}_j - P(y = i|\mathbf{x})\mathbf{z}_j & \text{if } i = i^* \\ -P(y = i|\mathbf{x})\mathbf{z}_j & \text{otherwise} \end{cases}$$



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

Neural Networks for Classification

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



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

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

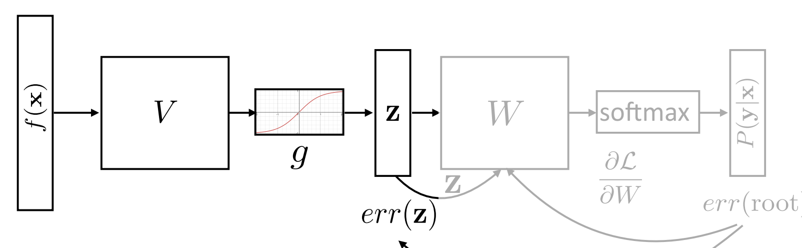
[some math…]

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

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

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: Takeaways

- Gradients of output weights *W* are easy to compute — looks like logistic regression with hidden layer ***z*** as feature vector
- Can compute derivative of loss with respect to ***z*** to form an "error signal" for backpropagation
- Easy to update parameters based on "error signal" from next layer, keep pushing error signal back as backpropagation
- Need to remember the values from the forward computation

Applications

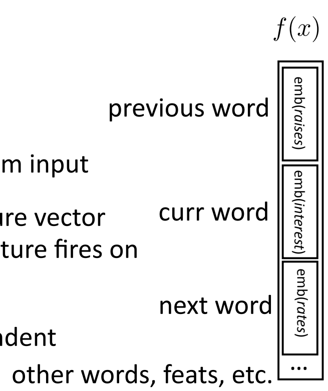
NLP with Feedforward Networks

- Part-of-speech tagging with FFNNs

??

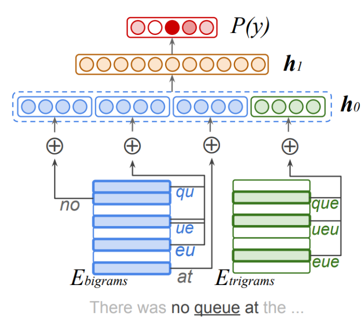
*Fed raises **interest** rates in order to …*

- Word embeddings for each word form input
- ~1000 features here — smaller feature vector than in sparse models, but every feature fires on every example
- Weight matrix learns position-dependent processing of the words



Botha et al. (2017)

NLP with Feedforward Networks



- Hidden layer mixes these different signals and learns feature conjunctions

Botha et al. (2017)

NLP with Feedforward Networks

- Multilingual tagging results:

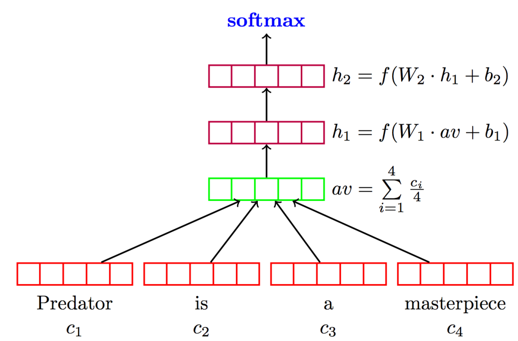
Model	Acc.	Wts.	MB	Ops.
Gillick et al. (2016)	95.06	900k	-	6.63m
Small FF	94.76	241k	0.6	0.27m
+Clusters	95.56	261k	1.0	0.31m
$\frac{1}{2}$ Dim.	95.39	143k	0.7	0.18m

- Gillick used LSTMs; this is smaller, faster, and better

Botha et al. (2017)

Sentiment Analysis

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



Iyyer et al. (2015)

Sentiment Analysis

	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	Iyyer et al. (2015)
Bag-of-words	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	—	Wang and Manning (2012)
Tree RNNs / CNNS / LSTMS	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	Kim (2014)
	WRRBM*	—	—	—	89.2	—	

Implementation Details

Computation Graphs

- Computing gradients is hard! Computation graph abstraction allows us to define a computation symbolically and will do this for us
- Automatic differentiation: keep track of derivatives / be able to backpropagate through each function:

```
y = x * x   --codegen-->   (y,dy) = (x * x, 2 * x * dx)
```

- Use a library like Pytorch or Tensorflow. This class: Pytorch

Computation Graphs in Pytorch

- Define forward pass for $P(\mathbf{y}|\mathbf{x}) = \mathrm{softmax}(Wg(Vf(\mathbf{x})))$

```
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)

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

Computation Graphs in Pytorch

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

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

```
ffnn = FFNN()
def make_update(input, gold_label):
   ffnn.zero_grad() # clear gradient variables
   probs = ffnn.forward(input)
   loss = torch.neg(torch.log(probs)).dot(gold_label)
   loss.backward()
   optimizer.step()
```

Training a Model

Define a computation graph

For each epoch:

For each batch of data:

Compute loss on batch

Autograd to compute gradients

Take step with optimizer

Decode test set

Next Time

- Training neural networks
- Word representations / word vectors
- word2vec, GloVe