Language Modeling

$+$

Feed-Forward Networks 3

CS 287

Review: LM ML Setup

Multi-class prediction problem,

$$(\mathbf{x}_1, \mathbf{y}_1), \ldots, (\mathbf{x}_n, \mathbf{y}_n)$$

- $\mathbf{y}_i$; the one-hot next word
- $\mathbf{x}_i$; representation of the prefix $(w_1, \ldots, w_{t-1})$

Challenges:

- How do you represent input?
- Smoothing is crucially important.
- Output space is very large (next class)

Review: Perplexity

Previously, used *accuracy* as a metric.

Language modeling uses of version average negative log-likelihood

- For test data $\bar{w}_1, \ldots, \bar{w}_n$
- $$NLL = -\frac{1}{n}\sum_{i=1}^{n} \log p(w_i | w_1, \ldots, w_{i-1})$$

Actually report *perplexity*,

$$perp = \exp(-\frac{1}{n}\sum_{i=1}^{n} \log p(w_i | w_1, \ldots, w_{i-1}))$$

Requires modeling full distribution as opposed to argmax (hinge-loss)

Review: Interpolation (Jelinek-Mercer Smoothing)

Can write recursively,

$$p_{interp}(w|c) = \lambda p_{ML}(w|c) + (1-\lambda) p_{interp}(w|c')$$

Ensure that λ form convex combination

$$0 \leq \lambda \leq 1$$

How do you learn conjunction combinations?

Quiz

Assume we have seen the following training sentences,

- a tractor drove slow
- the red tractor drove fast
- the parrot flew fast
- the parrot flew slow
- the tractor slowed down

Compute p_{ML} for bigrams and use them to estimate whether *parrot* or *tractor* fit better in the following contexts.

1. the red ___ ?
2. the ___ ?
3. the ___ drove?

Answer I

a	tractor	1
the	red	$\frac{1}{4}$
the	parrot	$\frac{1}{2}$
the	tractor	$\frac{1}{4}$
red	tractor	1
tractor	drove	$\frac{2}{3}$
tractor	slowed	$\frac{1}{3}$
parrot	flew	1
...		

Answer II

- the red tractor
- the parrot
- the tractor drove

Today's Class

$$p(w_i | w_{i-n+1}, \ldots w_{i-1}; \theta)$$

- Estimate this directly as a neural network.
- Two types of models, neural network and log-bilinear.
- Efficient methods for approximated estimation.

Intuition: NGram Issues

In training we might see,

the arizona corporations commission authorized

But at test we see,

the colorado businesses organization ___

- Does this training example help here?
  - Not really. No count overlap.
- Does backoff help here?
  - Maybe, if we have seen organization.
  - Mostly get nothing from the earlier words.

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Goal

- Learn representations that share properties between similar words.
- Particularly helpful for unseen contexts.
- Not a silver bullet, e.g. proper nouns

  the eagles play the arizona diamondbacks

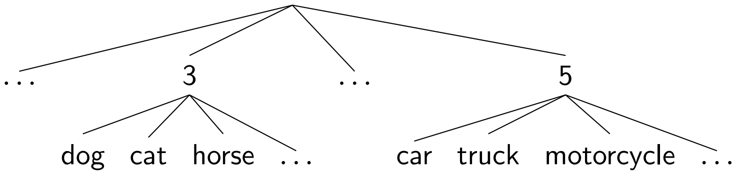
  Whereas at test we might see,

  the eagles play the colorado ___

  (We will discuss this issue more for in MT)

Baseline: Class-Based Language Models

- Groups words into classes based on word-context.



- Various factorization methods for estimating with count-based approaches.
- However, assumes a hard-clustering, often estimated separately.

Contents

Recall: Word Embeddings

- Embeddings give multi-dimensional representation of words.
- Ex: Closest by cosine similarity

arizona	texas	0.932968706025
	florida	0.932696958878
	kansas	0.914805968271
	colorado	0.904197441085
	minnesota	0.863925347525
	carolina	0.862697751337
	utah	0.861915722889
	miami	0.842350326527
	oregon	0.842065064748

- Gives a multi-clustering over words.

Feed-Forward Neural NNLM (Bengio, 2003)

- $w_{i-n+1}, \ldots w_{i-1}$ are input embedding representations
- w_i is an output embedded representation
- Model simultaneously learns,
  - input word representations
  - output word representations
  - conjunctions of input words (through NLM, no n-gram features)

Feed-Forward Neural Representation

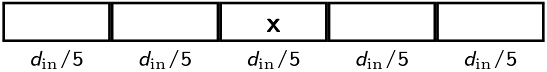
- $p(w_i | w_{i-n+1}, \dots w_{i-1}; \boldsymbol{\theta})$
- $f_1, \dots, f_{d_{\mathrm{win}}}$ are words in window
- Input representation is the concatenation of embeddings

$$\mathbf{x} = [v(f_1) \ v(f_2) \ \dots \ v(f_{d_{\mathrm{win}}})]$$

Example: NNLM ($d_{\mathrm{win}} = 5$)

$$[w_3 \ w_4 \ w_5 \ w_6 \ w_7] \ w_8$$

$$\mathbf{x} = [v(w_3) \ v(w_4) \ v(w_5) \ v(w_6) \ v(w_7)]$$



A Neural Probabilistic Language Model (Bengio, 2003)

One hidden layer multi-layer perceptron architecture,

$$NN_{MLP1}(\mathbf{x}) = \tanh(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1)\mathbf{W}^2 + \mathbf{b}^2$$

Neural network architecture on top of concat.

$$\hat{\mathbf{y}} = \text{softmax}(NN_{MLP1}(\mathbf{x}))$$

Best model uses $d_{\mathrm{in}} = 30 \times d_{\mathrm{win}}, d_{\mathrm{hid}} = 100$.

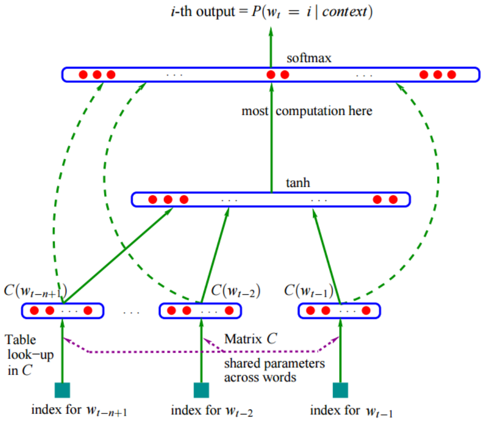
A Neural Probabilistic Language Model

Optional, direct connection layers,

$$NN_{DMLP1}(\mathbf{x}) = [\tanh(\mathbf{x}\mathbf{W}^1 + \mathbf{b}^1), \mathbf{x}]W^2 + \mathbf{b}^2$$

- $\mathbf{W}^1 \in \mathbb{R}^{d_{\text{in}} \times d_{\text{hid}}}$, $\mathbf{b}^1 \in \mathbb{R}^{1 \times d_{\text{hid}}}$; first affine transformation
- $\mathbf{W}^2 \in \mathbb{R}^{(d_{\text{hid}} + d_{\text{in}}) \times d_{\text{out}}}$, $\mathbf{b}^2 \in \mathbb{R}^{1 \times d_{\text{out}}}$; second affine transformation

A Neural Probabilistic Language Model (Bengio, 2003)



Dashed-lines show the optional direct connections, $C = v$.

A Neural Probabilistic Language Model

	n	c	h	m	direct	mix	train.	valid.	test.
MLP1	5		50	60	yes	no	182	284	268
MLP2	5		50	60	yes	yes		275	257
MLP3	5		0	60	yes	no	201	327	310
MLP4	5		0	60	yes	yes		286	272
MLP5	5		50	30	yes	no	209	296	279
MLP6	5		50	30	yes	yes		273	259
MLP7	3		50	30	yes	no	210	309	293
MLP8	3		50	30	yes	yes		284	270
MLP9	5		100	30	no	no	175	280	276
MLP10	5		100	30	no	yes		265	**252**
Del. Int.	3						31	352	336
Kneser-Ney back-off	3							334	323
Kneser-Ney back-off	4							332	321
Kneser-Ney back-off	5							332	321
class-based back-off	3	150						348	334
class-based back-off	3	200						354	340
class-based back-off	3	500						326	**312**
class-based back-off	3	1000						335	319
class-based back-off	3	2000						343	326
class-based back-off	4	500						327	312
class-based back-off	5	500						327	312

Parameters

- Bengio NNLM has $d_{\mathrm{hid}} = 100$, $d_{\mathrm{win}} = 5$, $d_{\mathrm{in}} = 5 \times 50$
- In-Class: How many parameters does it have? How does this compare to Kneser-Ney smoothing?

Historical Note

- Bengio et al notes that many of these aspects predate the work
- Furthermore proposes many of the ideas that Collobert et al. and word2vec implement and scale
- Around this time, very few NLP papers on NN, most-cited papers are about conditional random fields (CRFs).

Log-Bilinear Language Model (Mnih & Hinton, 2007)

Slightly different input representation. Now let:

$$\mathbf{x} = \sum_{i=1}^{d_{\mathrm{win}}} v(f_i)\mathbf{C}_i$$

- Instead of concatenating, weight each $v(f_i)$ by position-specific weight matrix $\mathbf{C}_i$.

Then use:

$$\hat{\mathbf{y}} = \mathrm{softmax}(\mathbf{x}\mathbf{W}^1 + \mathbf{b})$$

- Note no tanh layer.
- $\mathbf{W}^1$ can use input embeddings too, or not (Mnih and Teh, 2012)
- Can be faster to use, and in some cases simpler.

Comparison

Both count-based models and feed-forward NNLMs are Markovian language models,

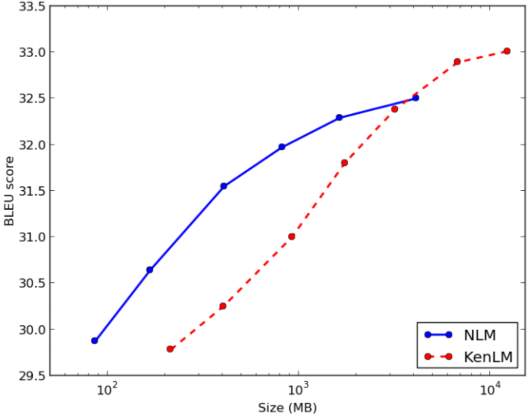
Comparison:

- Training Speed: ngrams are much faster (more coming)
- Usage Speed: ngrams very fast, NN can be fast with some tricks.
- Memory: NN models can be much smaller (but there are big ones)
- Accuracy: Comparable for small data, NN does better with more.

Advantages of NN model

- Can be trained end-to-end.
- Does not require smoothing methods.

Translation Performance (and Blunsom, 2015)



Contents

Review: Softmax Issues

Use a softmax to force a distribution,

$$\mathrm{softmax}(\mathbf{z}) = \frac{\exp(\mathbf{z})}{\sum_{w \in \mathcal{C}} \exp(z_w)}$$

$$\log \mathrm{softmax}(\mathbf{z}) = \mathbf{z} - \log \sum_{w \in \mathcal{C}} \exp(z_w)$$

- **Issue:** class $\mathcal{C}$ is huge.
- For C&W, 100,000, for word2vec 1,000,000 types
- Note largest dataset is 6 billion words

Unnormalized Scores

Recall the score defined as (dropping bias)

$$\mathbf{z} = \tanh(\mathbf{x}\mathbf{W}^1)\mathbf{W}^2$$

Unnormalized score of each word before soft-max,

$$z_j = \tanh(\mathbf{x}\mathbf{W}^1)\mathbf{W}^2_{*,j}$$

for any $j \in \{1, \dots d_{\mathrm{out}}\}$

Note: can be computed efficiently $O(1)$ versus $O(d_{\mathrm{out}})$.

Coherence

- Saw similar idea earlier for ranking embedding.
- **Idea:** Learn to distinguish coherent n-grams from corruption.
- Want to discriminate correct next words from other choices.

[the dog walks]

[the dog house]

[the dog cats]

[the dog skips]

Warm-Up

Imagine we have a new dataset,

$$((\mathbf{x}_1, \mathbf{y}_1), \mathbf{d}_1), \ldots, ((\mathbf{x}_n, \mathbf{y}_n), \mathbf{d}_n),$$

- $\mathbf{x}$; representation of context $w_{i-n+1}, \ldots w_{i-1}$
- $\mathbf{y}$; a possible w_i
- d; 1 if $\mathbf{y}$ is correct, 0 otherwise

Objective is based on predicted $\hat{d}$:

$$\mathcal{L}(\theta) = \sum_i L_{crossentropy}(d_i, \hat{d}_i)$$

Warm-Up: Binary Classification

How do we score $(\mathbf{x}_i, \mathbf{y}_i = \delta(w))$?

Could use unnormalized score,

$$z_w = \tanh(\mathbf{x}\mathbf{W}^1)\mathbf{W}^2_{*,c}$$

Becomes softmax regression/non-linear logistic regression,

$$\hat{d} = \sigma(z_w)$$

- Much faster
- But does not help us train LM.

Implementation

Standard MLP language model, (only takes in $\mathbf{x}$)

$$\mathbf{x} \Rightarrow \mathbf{W}^1 \Rightarrow \tanh \Rightarrow \mathbf{W}^2 \Rightarrow \text{softmax}$$

Computing binary (takes in $\mathbf{x}$ and $\mathbf{y}$)

$$\hat{d} = \sigma(z_w)$$

$$\mathbf{x} \Rightarrow \mathbf{W}^1 \Rightarrow \tanh \Rightarrow \underset{\mathbf{W}^2_{*,w}(\text{Lookup})}{\cdot} \Rightarrow \sigma$$

Noise Contrastive Estimation 1

Probabilistic model,

- Introduce random variable D
- If $D = 1$ produce true sample
- If $D = 0$ produce sample from a noise distribution.
- Hyperparameter K is ratio of noise

$$p(D = 1) = \frac{1}{K + 1}$$

$$p(D = 0) = \frac{K}{K + 1}$$

Noise Contrastive Estimation 2

For a given $\mathbf{x}, \mathbf{y}$,

$$
\begin{aligned}
p(D=1|\mathbf{x},\mathbf{y}) &= \frac{p(\mathbf{y}|D=1,\mathbf{x})p(D=1|\mathbf{x})}{\sum_d p(\ \mathbf{y}|D=d,\mathbf{x})p(D=d|\mathbf{x})} \\
&= \frac{p(\mathbf{y}|D=1,\mathbf{x})p(D=1|\mathbf{x})}{p(\mathbf{x}|D=0)p(D=0|\mathbf{x}) + p(\mathbf{y}|D=1,\mathbf{x})p(D=1|\mathbf{x})}
\end{aligned}
$$

Plug-in the noise distribution and hyperparameters,

$$
\begin{aligned}
p(D=1|\mathbf{x},\mathbf{y}) &= \frac{\frac{1}{K+1}p(\mathbf{y}|D=1,\mathbf{x})}{\frac{1}{K+1}p(\mathbf{y}|D=1,\mathbf{x}) + \frac{K}{K+1}p(\mathbf{y}|D=0,\mathbf{x})} \\
&= \frac{p(\mathbf{y}|D=1,\mathbf{x})}{p(\mathbf{y}|D=1,\mathbf{x}) + Kp(\mathbf{y}|D=0,\mathbf{x})} \\
&= \sigma(\log p(\mathbf{y}|D=1,\mathbf{x}) - \log(Kp(\mathbf{y}|D=0,\mathbf{x})))
\end{aligned}
$$

Noise Contrastive Estimation 3

With

$$p(D=1|\mathbf{x},\mathbf{y}) = \sigma(\log p(\mathbf{y}|D=1,\mathbf{x}) - \log(Kp(\mathbf{y}|D=0,\mathbf{x})))$$

we the training objective for a corpus that has K noise samples $s_{i,k}$ per example is:

$$\begin{aligned}
\mathcal{L}(\theta) &= \sum_i \log p(D=1|\mathbf{x}_i,\mathbf{y}_i) + \sum_{k=1}^{K} \log p(D=0|\mathbf{x}_i, Y=s_{i,k}) \\
&= \sum_i \log \sigma\left(\log p(\mathbf{y}_i|D=1,\mathbf{x}_i) - \log(Kp(\mathbf{y}_i|D=0,\mathbf{x}_i))\right) \\
&+ \sum_{k=1}^{K} \log\left(1 - \sigma\left(\log p(s_{i,k}|D=1,\mathbf{x}_i) - \log(Kp(s_{i,k}|D=0,\mathbf{x}_i))\right)\right)
\end{aligned}$$

- In practice, sample $s_{i,k}$ from unigram distribution

Noise Contrastive Estimation 4

But we still have a problem: $\mathcal{L}$ defined in terms of normalized distributions $\log p(\mathbf{y}|D = 1, \mathbf{x})$

Solution:

- instead of explicitly normalizing, estimate $Z(\mathbf{x})$, normalizing constant of each context $\mathbf{x}$, *as a parameter* (Gutmann & Hyvärinen, 2010)
- Mnih and Teh (2012) show that fixing $Z(\mathbf{x}) = 1$ for all contexts works just as well
- So we can replace $\log p(\mathbf{y} = \delta(w)|D = 1, \mathbf{x})$ with z_w, as computed by our network

Noise Contrastive Estimation 5

So we now have

$$
\begin{aligned}
\mathcal{L}(\theta) &= \sum_i \log \sigma(z_{w_i} - \log(Kp_{ML}(w_i))) \\
&+ \sum_{k=1}^{K} \log(1 - \sigma(z_{s_{i,k}} - \log(Kp_{ML}(s_{i,k}))))
\end{aligned}
$$

- Mnih and Teh (2012) show that gradient of $\mathcal{L}$ approaches gradient of true language model's log-likelihood objective as $k \to \infty$.

Implementation

- How do you efficiently compute z_w?

  Need a lookup table (and dot-product) for output embeddings!

  (Not full matrix-vector product).
- How do you efficiently handle $\log p_{ML}(w)$

  Can be precomputed or placed in a lookuptable .
- How do you handle sampling?

  Can precompute large number of samples (not example specific).
- How do you handle loss?

  Simply BinaryNLL Objective.

Implementation

Standard MLP language model,

$$\mathbf{x} \Rightarrow \mathbf{W}^1 \Rightarrow \tanh \Rightarrow \mathbf{W}^2 \Rightarrow \text{softmax}$$

Computing $\sigma(z_w - \log(K p_{ML}(w)))$,

$$\mathbf{x} \Rightarrow \mathbf{W}^1 \Rightarrow \tanh \Rightarrow \underset{\mathbf{W}^2_{*,w}(\text{Lookup})}{\cdot} \Rightarrow \underset{\log K p_{ML}(w)(\text{input})}{-} \Rightarrow \sigma$$

(Efficiency, compute first three layers only once for $K+1$)

Using in Practice

Several options for test time,

- Use full softmax with learned parameters.
- Compute subset of scores and renormalize (homework) .
- Can sometimes just use treat unormalized params as being normalized (self-normalization)