A Neural Probabilistic Language Model

Paper Presentation (Y Bengio, et. al. 2003)

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Table of Contents

Review of Language Models

- Predict $P(w_1^T) = P(w_1, w_2, w_3, \ldots, w_T)$
  - As a conditional probability: $P(w_1^T) = \prod_{i=1}^{T} P(w_t | w_1^{t-1})$

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  - As a conditional probability: $P(w_1^T) = \prod_{i=1}^{T} P(w_t | w_1^{t-1})$
  - Too many conditional probabilities! Simplify using n-gram model:
  - $P(w_t | w_1^T) \approx P(w_t | w_{T-n+1}^T)$

Problems

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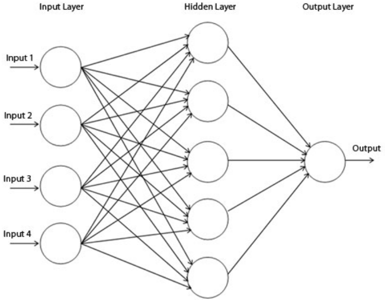
Problems

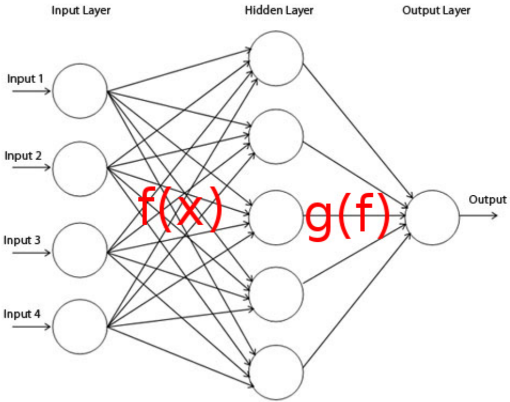
- We want to optimize on large n, but vocabulary size $V > 100000$.
- State of the art (as of 2003) was to use 2 or 3-gram models.
  - 10 gram models has $100000^{10} - 1 = 10^{50} - 1$ parameters
- Does not take in account of similarity between words
  - *A cat is walking in the bedroom*
  - *The dog was running in a room*

Table of Contents

Neural Networks

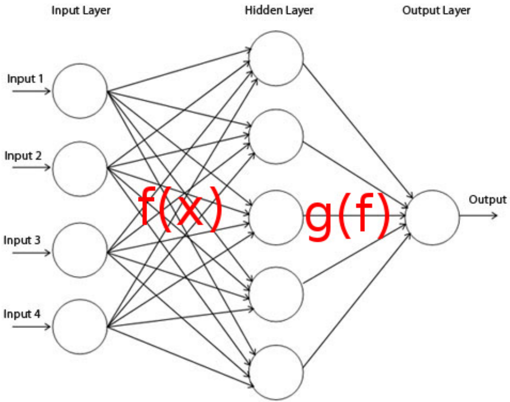


Neural Networks



$f : \mathbb{R}^4 \to \mathbb{R}^5$; Example: $F_1(x) = f(\mathbf{x}) = tanh(\mathbf{A}\mathbf{x})$, $\mathbf{A} \in \mathbb{R}^{5\times 4}$
$g : \mathbb{R}^5 \to \mathbb{R}$; Example: $F_2(x) = g(\mathbf{x}) = tanh(\mathbf{B}\mathbf{x})$, $\mathbf{B} \in \mathbb{R}^{1\times 5}$

Neural Networks



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A and **B** are parameters! Our network is just $F(\mathbf{x}) = F_2(F_1(\mathbf{x}))$

Table of Contents

Neural Network

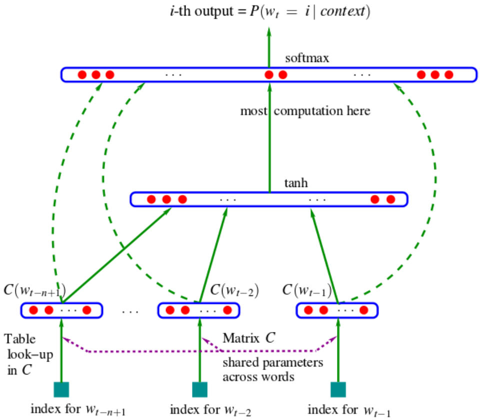
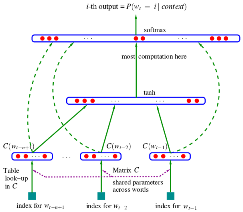


Figure 1: Neural architecture: $f(i, w_{t-1}, \cdots, w_{t-n+1}) = g(i, C(w_{t-1}), \cdots, C(w_{t-n+1}))$ where g is the neural network and $C(i)$ is the i-th word feature vector.

Model



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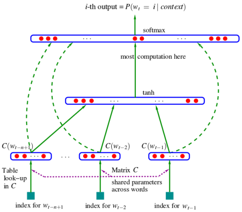
$$\hat{P}(w_t = i | w_1^{t-1}) = f(i, g(w_{t-n+1}^{t-1}))$$

Model



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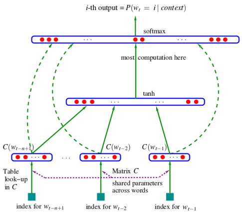
$g(w_1^t) = (C(w_1), C(w_2), \ldots C(w_T))$

$C(w_i)$ gives the w_i-th row of $|V| \times m$ matrix

"Lookup table"

Model



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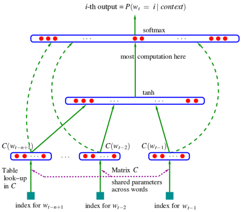
$$y(x) = b + Wx + U \tanh(d + Hx)$$
$$s(x) = \frac{e^x}{\sum_i (e^x)_i}$$
$$f(i, x) = s(y(x))_i$$

H is a $h \times (n-1)m$ matrix
d is a h length vector
U is a $|V| \times h$ matrix
W is a $|V| \times (n-1)m$ matrix
b is a $|V|$ length vector

Model



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$\hat{P}(w_t = i | w_1^{t-1}) = s(y(C(w_{t-n+1}^{t-1})))_i$

Parameters: $\theta = (b, d, W, U, H, C)$

$O(|V|(nm + h))$ parameters

Linear in n-gram size and vocab size!

Table of Contents

Training

$$\theta \leftarrow \theta + \epsilon \frac{\partial \hat{P}}{\partial \theta}$$

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- $\frac{\partial \hat{P}}{\partial \theta}$ can be found analytically using the chain rule
- ϵ is the learning rate

Data Parallelism

- Assume shared memory processor, communication costs are low
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- Split data up and have each CPU update the parameters
  - trick: asynchronously update parameters
  - May lose parameters, but occasional noise did not impact performance

Parameter Parallelism

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- Limiting factor during computation of $f(i,x) = s(y(x))_i = s(b + Wx + U\tanh(d + Hx))_i$

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  $f(i,x) = s(y(x))_i = s(b + Wx + U \tanh(d + Hx))_i$
  - Every processor computes $g(x)$.
  - i-th processor computes i-th block of $y(x)$
  - Update central server with sum, receive sum across $y(x)$.

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  - Update central server with sum, receive sum across $y(x)$.
- 99.7% calculations not repeated
- $\frac{1}{15}$ total time spent during network communications

Table of Contents

Brown Corpus

- 1,181,041 different words from english texts and books
- 47578 different words, including case, and puctuation.
- $|V| = 16383$ after introducing "rare words" symbol
  - no words with frequency less than 4

Brown Corpus

	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

Table 1: Comparative results on the Brown corpus. The deleted interpolation trigram has a test perplexity that is 33% above that of the neural network with the lowest validation perplexity. The difference is 24% in the case of the best n-gram (a class-based model with 500 word classes). n : order of the model. c : number of word classes in class-based n-grams. h : number of hidden units. m : number of word features for MLPs, number of classes for class-based n-grams. *direct*: whether there are direct connections from word features to outputs. *mix*: whether the output probabilities of the neural network are mixed with the output of the trigram (with a weight of 0.5 on each). The last three columns give perplexity on the training, validation and test sets.

AP News

- Associated press news from 1995-1996.
- ~14 million words
- 148,721 different words
- $|V| = 17964$
  - No words with frequency < 4.
  - Preprocessed to lower case
  - Preprocessed numbers, rare words, and proper nouns to special symbols

AP News

	n	h	m	direct	mix	train.	valid.	test.
MLP10	6	60	100	yes	yes		104	**109**
Del. Int.	3						126	132
Back-off KN	3						121	127
Back-off KN	4						113	119
Back-off KN	5						112	**117**

Table 2: Comparative results on the AP News corpus. See the previous table for the column labels.