Machine Learning (CS 181):
13. Topic Lecture
Neural Networks for Language

David Parkes and Sasha Rush

Contents

It is a capital mistake to theorize before one has data. Insensibly one begins to twist facts to suit theories, instead of theories to suit facts. -Sherlock Holmes, A Scandal in Bohemia

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It is a capital mistake to theorize before one has ______ . . .

108 938 285 28 184 29 593 219 58 772 ______ . . .

Language Modeling Task

Given a sequence of text give a probability distribution over the next word.

The Shannon game. Estimate the probability of the next letter/word given the previous.

> *THE ROOM WAS NOT VERY LIGHT A SMALL OBLONG READING LAMP ON THE DESK SHED GLOW ON POLISHED ___*

Mathematical Model of Communication

- Shannon (1948)

  We may consider a discrete source, therefore, to be represented by a stochastic process. Conversely, any stochastic process which produces a discrete sequence of symbols chosen from a finite set may be considered a discrete source. This will include such cases as:

  1. Natural written languages such as English, German, Chinese. ...

Shannon's Babblers I

4. Third-order approximation

IN NO 1ST LAT WHEY CRATICT FROURE BIRS GROCID PONDENOME OF DEMONSTURES OF THE REPTAGIN IS REGOACTIONA OF CRE

5. First-Order Word Approximation. Rather than continue with tetragram, ... , II-gram structure it is easier and better to jump at this point to word units. Here words are chosen independently but with their appropriate frequencies.

REPRESENTING AND SPEEDILY IS AN GOOD APT OR COME CAN DIFFERENT NATURAL HERE HE THE A IN CAME THE TO OF TO EXPERT GRAY COME TO FURNISHES THE LINE MESSAGE HAD BE THESE.

Shannon's Babblers II

6. Second-Order Word Approximation. The word transition probabilities are correct but no further structure is included.
THE HEAD AND IN FRONTAL ATTACK ON AN ENGLISH 'RITER THAT THE CHARACTER OF THIS POINT IS THEREFORE ANOTHER METHOD FOR THE LETTERS THAT THE TIME OF WHO EVER TOLD THE PROBLEM FOR AN UNEXPECTED
The resemblance to ordinary English text increases quite noticeably at each of the above steps.

Language Modeling Applications

- Speech Recognition
- Machine Translation
- Summarization
- Dialogue
- Soft Keyboards
- Word Correction
- Text Simplification
- . . .

Contents

Language Modeling as Supervised Learning

THE ROOM WAS NOT VERY LIGHT A SMALL OBLONG READING LAMP ON THE DESK SHED GLOW ON POLISHED ___

- Sample pairs are $(\mathbf{x}, \mathbf{y})$.
- Input is sentence up until the blank, output is next word prediction.
- Challenging multi-class prediction problem, feature representation matters.
- Begin by considering count-based categorical prediction models:

$$p(\mathbf{y}|\mathbf{x})$$

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Word Representation

- We say the vocabulary of the language is $|\mathcal{V}|$
- In practice $|\mathcal{V}|$ is 10,000 - 100,000 unique words
- Each word has an associated numerical index.
- We represent each word as a one-hot vector C_k where $k \in \{1, \dots |\mathcal{V}|\}$

$$[0, 0, 0, 0, 0, 1, \dots, 0]$$

- For this problem, both input and output will use one-hot C_k vectors.

Input Representation

- Recall *bag-of-words* model, with $\mathbf{x}$ counts of words
- Why doesn't this work here?
- Alternative model, *bigram*, i.e. two words

  ~~THE ROOM WAS NOT VERY LIGHT A SMALL OBLONG READING LAMP ON THE DESK SHED GLOW ON~~ POLISHED ___

- $\mathbf{x}$ is one-hot vector $\mathbf{x} \in \{0,1\}^{|\mathcal{V}|}$ representing last word.
- What assumptions is this making?

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  ~~ON~~ POLISHED ___

- $\mathbf{x}$ is one-hot vector $\mathbf{x} \in \{0,1\}^{|\mathcal{V}|}$ representing last word.
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Output Representation

- Output is the next word which we predict based on the last word.
- Let $\mathcal{Y} = \{0, 1\}^{|\mathcal{V}|}$ be the set of all possible words as one-hot vectors.
- Notation $\mathbf{y} = C_k$ means correct output is word k.

Bigram Model

- What is the probability $p(\mathbf{y}|\mathbf{x})$ under a bigram distribution?
- Assume we have parameters for all possible inputs $\{\boldsymbol{\pi}_j\}$ and that C_j is the last word seen.
- Model as a categorical distribution:

$$p(\mathbf{y} = C_k \mid \mathbf{x} = C_j; \{\boldsymbol{\pi}_j\}) = \pi_{jk}$$

where for all j, $\pi_{jk} \geq 0$ and $\sum_{k=1}^{c} \pi_{jk} = 1$

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Bigram Model

Bigram model represents the probability of the next word $\mathbf{y}$ given the last word $\mathbf{x}$

$$p(\mathbf{y} = C_k \mid \mathbf{x} = C_j; \{\boldsymbol{\pi}_j\}) = \pi_{jk}$$

$\mathbf{x} \backslash \mathbf{y}$	the	dog	cat	horse	...
the	0	0.2	0.2	0.1	
dog	0	0	0	0	
cat	0	0.05	0	0	
horse	0	0	0	0	
⋮					

N-Gram Model

- Can extend $\mathbf{x}$ to include multiple previous words.
- For instance a *trigram* model uses,

  ON POLISHED ___

- For this model $\mathbf{x} \in \{0,1\}^{2\times|\mathcal{V}|}$.
- Note: this is different than bag-of-words, vector gets larger $[C_{j'}; C_j]$.

$$p(\mathbf{y} = C_k \mid \mathbf{x} = [C_{j'}; C_j]; \{\boldsymbol{\pi}_{j'j}\}) = \pi_{j'jk}$$

- Different weight vector for all pairs, $\boldsymbol{\pi}_{j'j}$

N-Gram Model

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$\mathbf{x}\backslash\mathbf{y}$	the	dog	cat	horse	...
on the	0	0.2	0.2	0.1	
by the	...				
with the	...				
near the	...				
$\vdots$					

Learning N-Gram Models

Ingredients:

- 1 Corpus (e.g. the entire web)

Steps:

- (1) Collect words, (2) Count up n-grams, (3) Divide*

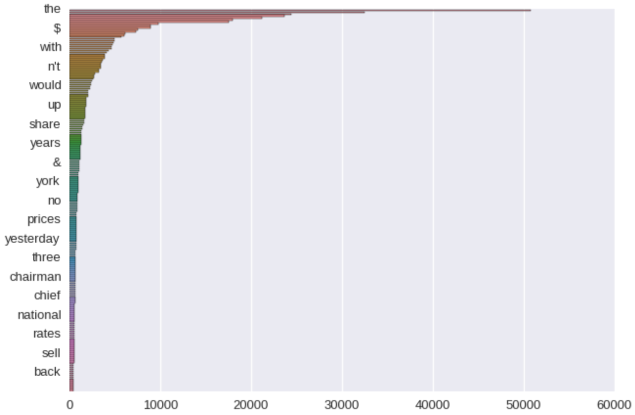
$$p(\mathbf{y}|\mathbf{x}) = \frac{\#(\mathbf{y}, \mathbf{x})}{\#(\mathbf{x})}$$

Google 1T

Number of token	1,024,908,267,229
Number of sentences	95,119,665,584
Size compressed (counts only)	24 GB
Number of unigrams	13,588,391
Number of bigrams	314,843,401
Number of trigrams	977,069,902
Number of fourgrams	1,313,818,354
Number of fivegrams	1,176,470,663

Zipf' Law (1935,1949)

The frequency of any word is inversely proportional to its rank in the frequency table.



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Intuition: N-Gram 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.

- Intuition: hope to learn that similar words act similarly.

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Alternative Approach

Consider now using neural networks for this prediction.

Two important ideas that we have seen so far.

1. Softmax for multiclass prediction of next word (out of $\mathcal{V}$)
2. Adaptive basis to learn representation of past words

Predicting the Next Word

- Recall: softmax approach for multi-class classification.

$$p(\mathbf{y} = C_k | \mathbf{x}; \{\mathbf{w}_\ell\}, \mathbf{W}^1) = \frac{\exp(\mathbf{w}_k^\top \boldsymbol{\phi}(\mathbf{x}; \mathbf{W}^1))}{\sum_\ell \exp(\mathbf{w}_\ell^\top \boldsymbol{\phi}(\mathbf{x}; \mathbf{W}^1))}$$

- The score term, gives the score for each output work C_k conditioned on some representation of the input.

$$\mathbf{w}_k^\top \boldsymbol{\phi}(\mathbf{x}; \mathbf{W}^1)$$

- Probability of word is softmax over these scores.
- Why might this be hard to compute?

Neural Networks

- Recall: Approach of neural networks has been to learn adaptive basis,

$$\boldsymbol{\phi}(\mathbf{x}; \mathbf{w}) = \sigma(\mathbf{W}^1 \mathbf{x} + \mathbf{w}_0^1)$$

- What would this look like for a bigram model?

$$\mathbf{x} = C_j$$

$$\mathbf{W}^1 \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} = \mathbf{W}^1_{\star, j}$$

- Returns just a column vector of the matrix.

Interpretation of Network

- Notation input $\mathbb{R}^m$ and basis $\mathbb{R}^d$.
- Unlike other problems here m is large $|\mathcal{V}|$ (10,000-100,000)
- But d can be much smaller. Why is that?

$$\mathbf{W}^1 \begin{bmatrix} 0 \\ 0 \\ 1 \\ \vdots \\ 0 \end{bmatrix} = \mathbf{W}^1_{\star,j}$$

- The output of this layer $\mathbf{W}^1_{\star,j} \in \mathbb{R}^d$ is called a *word vector*.

Sparse versus Distributed Representation

- Internally we have now seen two representations of words
- $\mathbf{x}$ Sparse: Very high dimensional, easy to get back the original word, but feature weights are not shared between words. $\mathbf{w}_j$ is weight for one word.

$$[0, 0, 0, 1, \ldots 0]$$

- $\phi(\mathbf{x})$ Distributed: Low dimensional but dense, each dimension is a feature of the word, $\mathbf{w}_j$ is weight for basis function.

$$[0.23, 0.32, 0.109, -0.1231, \ldots, 0.402]$$

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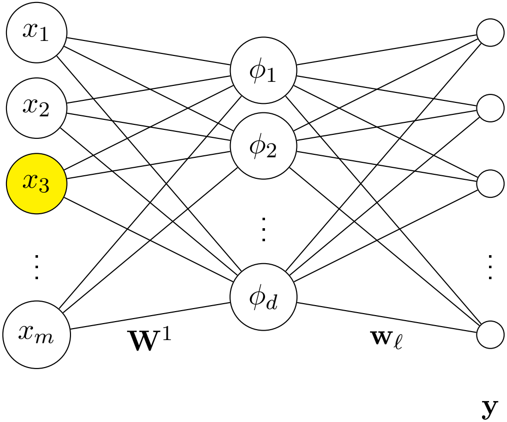


Depiction of the neural network. First layer is one-hot with $m = |\mathcal{V}|$. Hidden layer has $d << m$. Last layer is the score given to each possible output word. Original representation is sparse, and basis layer gives a *dense* representation of $\mathbf{x}$.

Word Vectors In Practice

- Word2Vec: famous pre-trained word vectors trained on Google News.
- Famous for learning a "linear" representation of words in $\mathbb{R}^d$

$$\phi(\text{king}) - \phi(\text{man}) + \phi(\text{woman}) \approx \phi(\text{queen})$$

- Vectors extracted from $\mathbf{W}^1$ after training for MLE on language model like task.

Example

Contents

History

THE ROOM WAS NOT VERY LIGHT A SMALL OBLONG READING LAMP ON THE DESK SHED GLOW ON POLISHED ___

Recall model is,

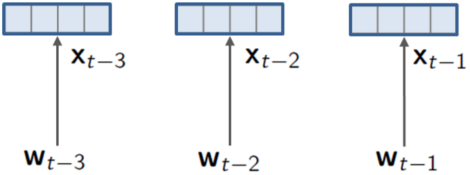
$$p(\mathbf{y}|\mathbf{x})$$

- So far we have assumed input $\mathbf{x}$ is fixed size n-grams.
- But with deep neural network basis we do not need to do this.
- *Recurrent neural networks* use all the context words.

Recurrent Neural Network Language Model

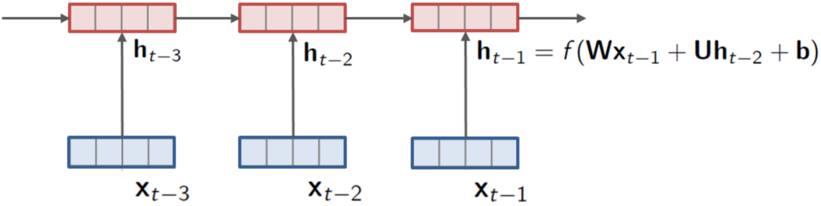
Word Vector	sparse input	$\Rightarrow$	dense basis
RNNs	sequences of basis	$\Rightarrow$	dense basis
Softmax	dense basis	$\Rightarrow$	discrete predictions

Word Vectors sparse input $\Rightarrow$ dense basis



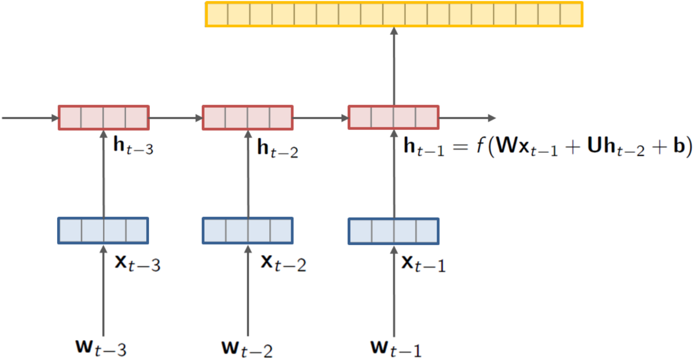
- First layer of the network maps from one-hot words to word vectors (using layer shown above).

RNNs/LSTMs sequences of basis functions $\Rightarrow$ dense basis



- Each word vector is connected together in a chain over time.
- $$\phi(\mathbf{x}, \mathbf{h}) = \sigma(\mathbf{W}^1\mathbf{x} + \mathbf{W'}^1\mathbf{h} + \mathbf{w}_0)$$

LM/Softmax dense features $\Rightarrow$ discrete predictions



$$p(\mathbf{y} = C_k | \mathbf{x}; \{\mathbf{w}_\ell\}, \mathbf{W}^1) = \frac{\exp(\mathbf{w}_k^\top \boldsymbol{\phi}(\mathbf{x}; \mathbf{W}^1))}{\sum_\ell \exp(\mathbf{w}_\ell^\top \boldsymbol{\phi}(\mathbf{x}; \mathbf{W}^1))}$$

- Here $\phi(\mathbf{x})$ encapsulates the red and blue parts of the network.

Contents

Application of RNNs

RNN models have lead to a **major** increase in the accuracy of language models.

Why did this matter?

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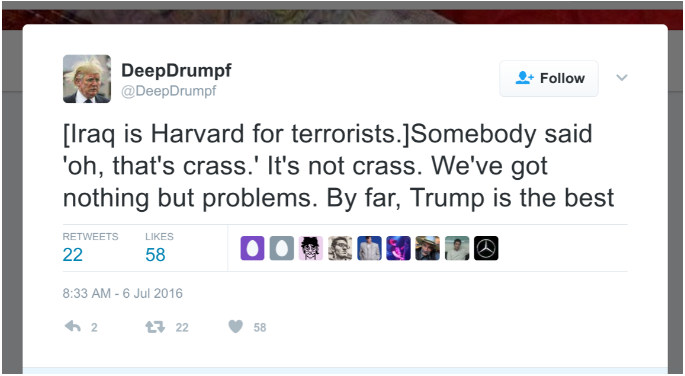
Why did this matter?



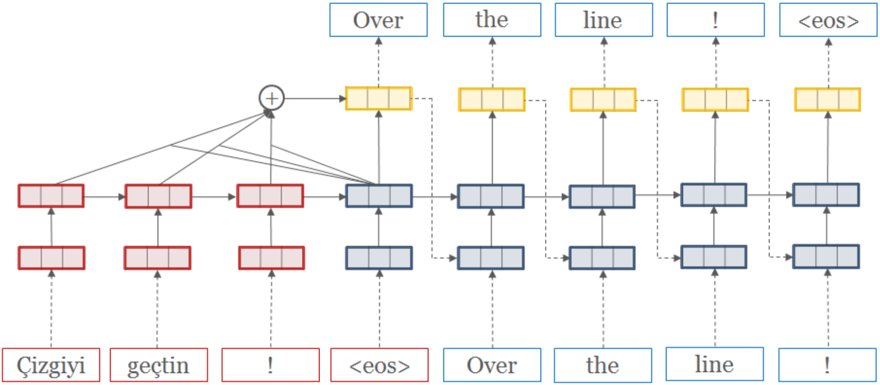
Sequence-to-Sequence

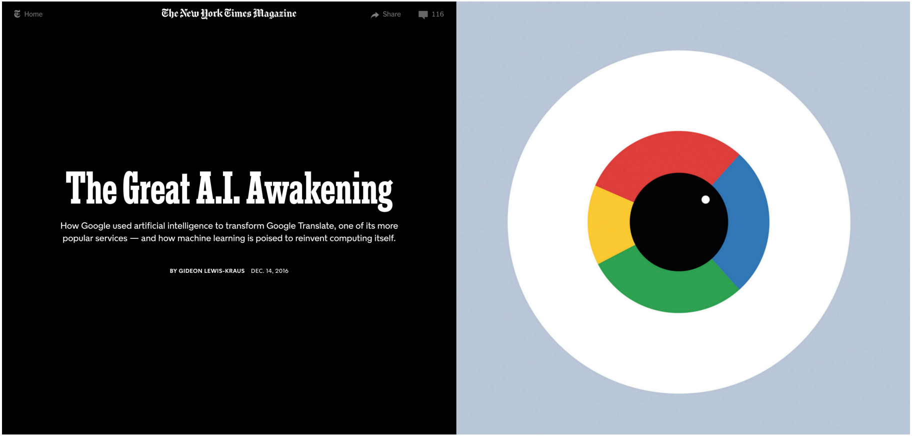
- Instead of just doing language model, also have basis functions for another input.
- For example, French-to-English translation:
  - Given a French sentence and previous English words, predict next English word

    $$p(\mathbf{y}|\mathbf{x})$$

    Where $\mathbf{y}$ is next English word.

Sequence-to-Sequence

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The New York Times Magazine

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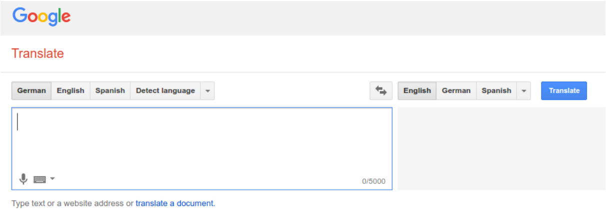
The Great A.I. Awakening

How Google used artificial intelligence to transform Google Translate, one of its more popular services — and how machine learning is poised to reinvent computing itself.

BY GIDEON LEWIS-KRAUS DEC. 14, 2016

Google Translate



- Completely replaced their machine translation systems.
- Accuracy significantly increased
- Reduced code size tremendously (rumor around 1K).

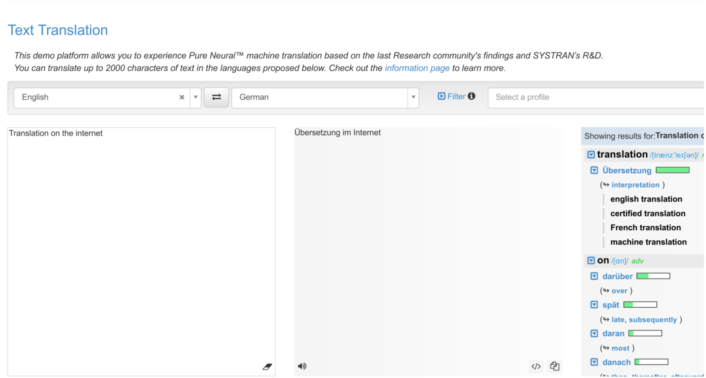
Applications

- Machine Translation
- Question Answering
- Conversation
- Parsing
- Speech
- Caption Generation
- Video-Generation
- NER/POS-Tagging
- Summarization

Contents

OpenNMT

- Our open-source system http://opennmt.net



[Demo]

Applications: Neural Summarization

Source (First Sentence)

Russian Defense Minister Ivanov called Sunday for the creation of a joint front for combating global terrorism.

Target (Title)

Russia calls for joint front against terrorism.

- Used by Washington Post to suggest headlines

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Source (Original Sentence)

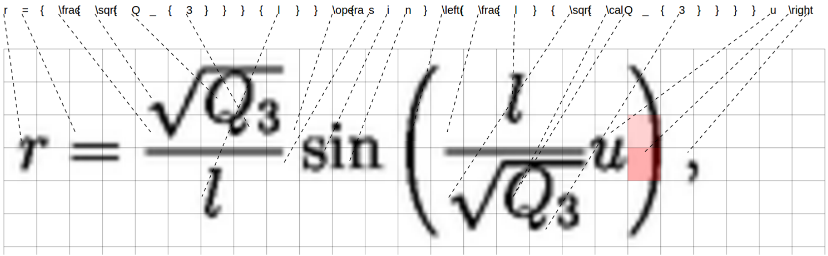
There is no a doubt, tracking systems has brought many benefits in this information age .

Target (Corrected Sentence)

There is no doubt, tracking systems have brought many benefits in this information age .

- 1st on BEA'11 grammar correction task

Applications: Im2Markup (Deng et al, 2017)



[Latex Example]

[Project]