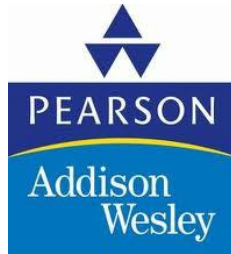


Neural Network Language Models

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Pearson



Supervised learning

\mathbb{X} Training matrix

\mathbb{Y} Target vector

\mathbf{x} Feature vector

$\hat{\mathbf{y}}$ Prediction

$$\mathbb{F}(\mathbb{X}, \mathbb{Y}) \rightarrow (\mathbf{f}(\mathbf{x}) \rightarrow \hat{\mathbf{y}})$$

Language models (LMs)

- Language as a sequence
- Tasks
 - Training
 - Learn joint probability of word given context
 - Predicting
 - Compute probability of word and context
 - Generate sequences

LMs are unsupervised

\mathbb{X} Sequences of words

\mathbf{x} A sequence of words $\mathbf{w} \mathbf{w}_{n-1} \dots$

$\hat{\mathbf{P}}(\mathbf{x})$ Probability of \mathbf{w} given context

$$\mathbb{F}(\mathbb{X}) \rightarrow (\mathbf{f}(\mathbf{x}) \rightarrow \hat{\mathbf{P}}(\mathbf{x}))$$

N-grams

Unigrams: N-grams with N=1.

$$P(w_n) = \frac{C(w_n)}{\sum_w C(w)}$$

N-grams

Bigrams: N-grams with N=2.

$$\begin{aligned} P(w_n | w_{n-1}) &= \frac{C(w_{n-1}w_n)}{\sum_w C(w_{n-1}w)} \\ &= \frac{C(w_{n-1}w_n)}{C(w_{n-1})} \end{aligned}$$

Trigrams, quadrigrams,

N-gram example

this is the way the |world ends

this is the way the **world ends**

this is the way the **ladies ride**

this is the way the **world ends dexter**

this is the way the **bunny hops song**

About 376,000,000 results (0.23 seconds)

not with a bang but a whimper

not with a **bang but a whimper**

not with a **club the heart is broken**

not with a **whisper but with a bang**

not with a **bang damon knight**

About 963,000 results (0.31 seconds)

N-gram example

| Phrase | Counts (Google) |
|--|-----------------|
| This is the way the world | 2,750,000 |
| This is the way the world ends | 1,920,000 |
| This is the way the world is | 537,000 |
| This is the way the world turns | 319,000 |
| This is the way the world works | 211,000 |
| This is the way the world bling | 0 |

N-gram example (cont.)

$$\begin{aligned}P(w|w_{n-1} \dots) &= P(\mathit{ends} \mid \mathit{this is the way the world}) \\ &= 1,920,000/2,750,000 \\ &= 0.69\end{aligned}$$

Evaluating LMs

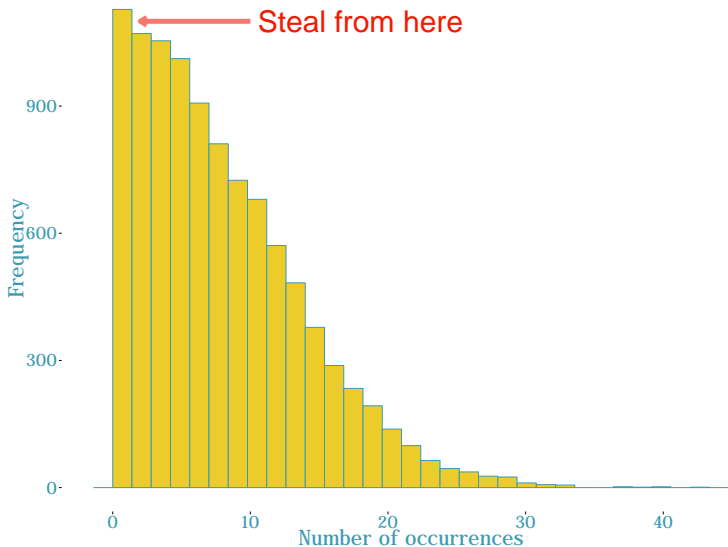
| Type | Loss function |
|----------------|---|
| Regressor | $\frac{1}{N} \sum (\mathbf{y} - \hat{\mathbf{y}})^2$ |
| Classifier | $\frac{1}{N} \sum \mathbf{I}(\mathbf{y}, \hat{\mathbf{y}})$ |
| Language model | $\sqrt[N]{\sum_{i=1}^N \frac{1}{P(\mathbf{w}_i \mathbf{w}_{i-1})}}$ |

A problem

N-grams that don't occur in the training set cause N-gram probability to go to 0.

$$\begin{aligned}P(w|w_{n-1} \dots) &= P(\mathbf{bling} \mid \mathbf{this is the way the world}) \\ &= 0/2,750,000 \\ &= 0\end{aligned}$$

Solution - Good-Turing



Solution - Backoff

3-gram ? \rightarrow 2-gram ? \rightarrow 1-gram ?

Solution - Interpolation

$$LM = \alpha_1 lm_1(\mathbf{w}_n \mathbf{w}_{n-1}) + \dots + \alpha_n lm_2(\mathbf{w}_n \mathbf{w}_{n-1})$$

Questions before moving to neural
network (NN) LMs?

NN LMs are different

\mathbb{X} Sequences of text

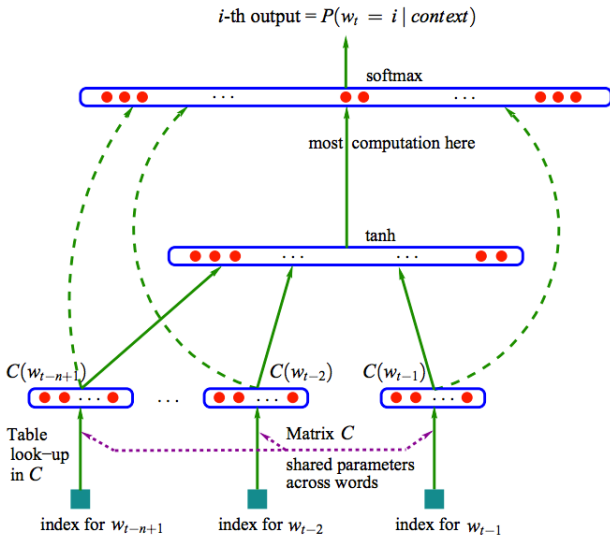
\mathbf{x} Sequence of text $\mathbf{w} \mathbf{w}_{n-1} \dots$

$\hat{P}(\mathbf{x})$ Probability of \mathbf{w} given context

\mathbf{W} Matrix of word representations

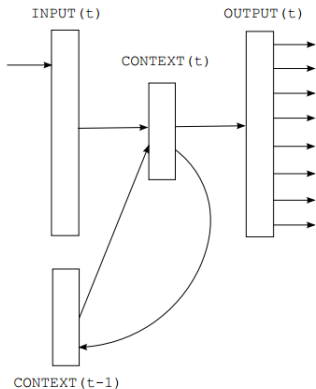
$$\mathbb{F}(\mathbb{X}) \rightarrow (\mathbf{f}(\mathbf{x}) \rightarrow \hat{P}(\mathbf{x}), \mathbf{W})$$

Early neural network LM



A Neural Probabilistic Language Model, Bengio et al, 2003

Recurrent neural network LM



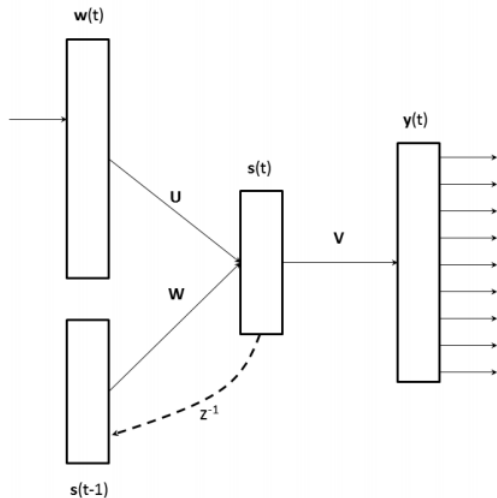
Recurrent neural network based language model, Mikolov et al, 2010

Recurrent neural network LM

| Model | # words | Perplexity |
|-----------|---------|------------|
| KN5 | 200K | 336 |
| KN5 + RNN | 200K | 271 |
| KN5 | 1M | 287 |
| KN5 + RNN | 1M | 225 |
| KN5 | 6.4M | 221 |
| KN5 + RNN | 6.4M | 156 |

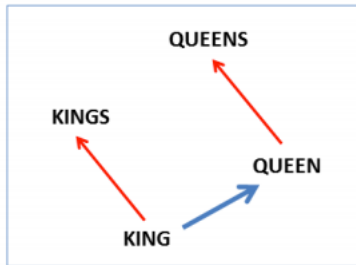
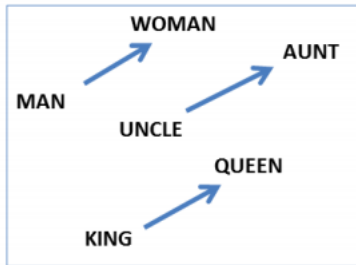
Performance on WSJ dev set.

Learning representations



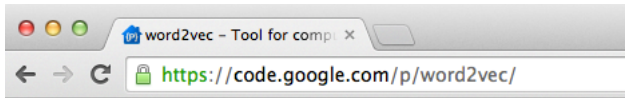
Linguistic Regularities in Continuous Space Word Representations, Mikolov et al, 2013

Properties of learned representations



Linguistic Regularities in Continuous Space Word Representations, Mikolov et al, 2013

A fast neural network LM



word2vec

Tool for computing continuous distributed representations of words.

Efficient Estimation of Word Representations in Vector Space, Mikolov et al, 2013

Also try [this online demo](#).

Questions?

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