Word Embeddings



Overview

- Representing meaning
- Word embeddings: Early work
- Word embeddings via language models
- Word2vec and Glove
- Evaluating embeddings
- Design choices and open questions

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Word embeddings via language models

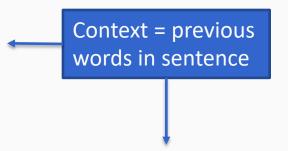
The goal: To find vector embeddings of words

High level approach:

- 1. Train a model for a surrogate task (in this case language modeling)
- 2. Word embeddings are a byproduct of this process

Neural network language models

- A multi-layer neural network [Bengio et al 2003]
 - Words → embedding layer → hidden layers → softmax
 - Cross-entropy loss



- Instead of producing probability, just produce a score for the next word (no softmax) [Collobert and Weston, 2008]
 - Ranking loss
 - Intuition: Valid word sequences should get a higher score than invalid ones
- No need for a multi-layer network, a shallow network is good enough [Mikolov, 2013, word2vec]
 - Simpler model, fewer parameters
 - Faster to train

Context = previous and next words in sentence

This lecture

The word2vec models: CBOW and Skipgram

Connection between word2vec and matrix factorization

GloVe

Word2Vec

[Mikolov et al ICLR 2013, Mikolov et al NIPS 2013]

- Two architectures for learning word embeddings
 - Skipgram and CBOW
- Both have two key differences from the older Bengio/C&W approaches
 - 1. No hidden layers
 - 2. Extra context (both left and right context)

Several computational tricks to make things faster

This lecture

• The word2vec models: **CBOW** and Skipgram

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Train the model by minimizing loss over the dataset

$$L = -\sum \log P(x_0 \mid x_{-m}, \dots, x_{-1}, x_1, \dots, x_m)$$

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$$x_{-m}, \dots, x_{-1}, x_0, x_1, \dots, x_m$$

Define a probabilistic model for predicting the middle word

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Need to define this to complete the model

Train the model by minimizing loss over the dataset

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The classification task

- Input: context words x_{-m} , \cdots , x_{-1} , x_1 , \cdots , x_m
- Output: the center word x_0
- These words correspond to one-hot vectors
 - Eg: cat would be associated with a dimension, its one-hot vector has 1 in that dimension and zero everywhere else

Notation:

- n: the embedding dimension (eg 300)
- V: The vocabulary of words we want to embed

Define two matrices:

- 1. \mathcal{V} : a matrix of size $n \times |V|$
- 2. \mathcal{W} : a matrix of size $|V| \times n$

Input: context x_{-m} , ..., x_{-1} , x_1 , ..., x_m Output: the center word x_0 n: the embedding dimension (eg 300)

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Exercise: Write this as a computation graph

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Word embeddings = Rows of the matrix corresponding to the output. That is, rows of \mathcal{W}

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Consider the loss for one example with context size 2 on each side. Denote the words by a b c d e with c being the output

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More concretely:

$$P(c \mid a, b, d, e) = \frac{\exp(w_c^T \hat{v})}{\sum_{i=1}^{|V|} \exp(w_i^T \hat{v})}$$

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Connection between word2vec and matrix factorization

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Skipgram

The other word2vec model

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Inverts the inputs and outputs from CBOW

As far as the probabilistic model is concerned:

Input: the center word

Output: all the words in the context

The Skipgram model

The classification task

- Input: the center word x_0
- Output: context words x_{-m} , \dots , x_{-1} , x_1 , \dots , x_m
- As before, these words correspond to one-hot vectors

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3. Normalize the score for each position to get a probability

$$P(x_i = \cdot | x_0) = \operatorname{softmax}(v_i)$$

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Remember the goal of learning: Make this probability highest for the observed words in this context.

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$$P(x_i = \cdot | x_0 = c) = \text{softmax}(v)$$

Or more specifically:

$$P(x_{-2} = a \mid x_0 = c) = \frac{\exp(v_a^T w_c)}{\sum_{i=1}^{|V|} \exp(v_i^T w_c)}$$

Consider the loss for one example with context size 2 on each side. Denote the words by a b c d e with c being the output

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The loss for this example is the sum of the negative log of this over all the context words.

$$Loss = \sum_{k \in \{a,b,d,e\}} \left(-v_k^T w_c + \log \sum_{i=1}^{|V|} \exp(v_i^T w_c) \right)$$

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Negative sampling

$$\log \sum_{i=1}^{|V|} \exp(v_i^T w_c)$$

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Can we make it faster?

- Answer [Mikolov et al 2013]: change the objective function and define a new objective function that does not have the same problem
 - Negative Sampling
- The overall method is called Skipgram with Negative Sampling (SGNS)

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 - We can solve this using logistic regression
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 - That is, there are only k negatives for each positive example, instead of the entire vocabulary

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Word2vec notes

There are many other tricks that are needed to make this work and scale

- A scaling term in the loss function to ensure that frequent words do not dominate the loss
- Hierarchical softmax if you don't want to use negative sampling
- A clever learning rate schedule
- Very efficient code

See readings for more details

This lecture

The word2vec models: CBOW and Skipgram

Connection between word2vec and matrix factorization

GloVe

Recall: matrix factorization for embeddings

The general agenda

- 1. Construct a matrix word-word M whose entries are some function extracted from data involving words in context (e.g., counts, normalized counts, etc)
- 2. Factorize the matrix using SVD to produce lower dimensional embeddings of the words
- 3. Use one of the resulting matrices as word embeddings
 - Or some combination thereof

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1. The entries in the matrix are a <u>shifted positive pointwise mutual information</u> (SPPMI) between a word and its context word.

$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

These probabilities are computed by counting the data and normalizing them

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$$PMI(w,c) = \log \frac{p(w,c)}{p(w)p(c)}$$

$$SPPMI(w,c) = \max(0, PMI(w,c) - \log k)$$

[Levy and Goldberg, NIPS 2014]: Skipgram negative sampling is implicitly factorizing a specific matrix of this kind

Two key points to note:

- 2. The matrix factorization method is not truncated SVD.
 - It instead minimizes the objective function to compute the factorized matrices

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• GloVe [Pennington et al 2014]

What matrix to factorize?

If we are building word embeddings by factorizing a matrix, what matrix should we consider?

- Word counts [Rhode et al 2005]
- Shifted PPMI (implicitly) [Mikolov 2013, Levy & Goldberg 2014]
- Another answer: log co-occurrence counts [Pennington et al 2014]

Co-occurrence probabilities

Given two words i and j that occur in text, their co-occurrence probability is defined as the probability of seeing word i in the context of word j

$$P(j | i) = \frac{\text{count}(j \text{ in context of } i)}{\sum_{k} \text{count}(k \text{ in context of } i)}$$

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Given two words i and j that occur in text, their co-occurrence probability is defined as the probability of seeing word i in the context of word j

$$P(j \mid i) = \frac{\text{count}(j \text{ in context of } i)}{\sum_{k} \text{count}(k \text{ in context of } i)}$$

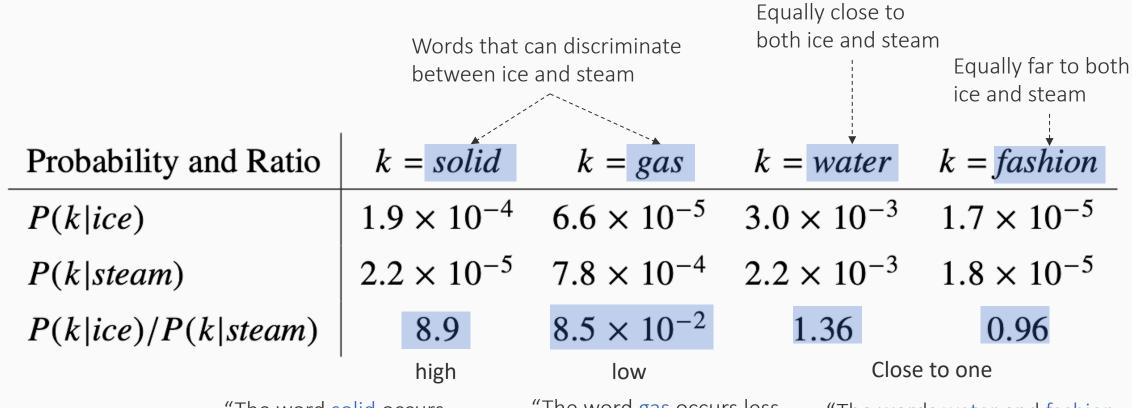
Claim: If we want to distinguish between two words, it is not enough to look at their co-occurrences, we need to look at the ratio of their co-occurrences with other words

Formalizing this intuition gives us an optimization problem

Co-occurrence ratios: An example

	Words that can discriminate between ice and steam		Equally close to both ice and stea	em Equally far to both ice and steam
Probability and Ratio	k = solid	k = gas	k = water	k = fashion
P(k ice)	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
P(k steam)	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	1.8×10^{-5}
P(k ice)/P(k steam)	8.9	8.5×10^{-2}	1.36	0.96

Co-occurrence ratios: An example



"The word solid occurs more frequently with ice than it does with steam" "The word gas occurs less frequently with ice than it does with steam"

"The words water and fashion occur about as frequently with ice than it does with steam"

Notation:

- *i* : word, *j* : a context word
- \mathbf{w}_i : The word embedding for i
- c_i : The context embedding for j
- b_i^w , b_i^c : Two bias terms: word and context specific
- X_{ij} : The number of times word i occurs in the context of j

The intuition:

- 1. Construct a word-context matrix whose $(i,j)^{th}$ entry is $\log X_{ij}$
- 2. Find vectors \mathbf{w}_i , \mathbf{c}_j and the biases b_i , c_j such that the dot product of the vectors added to the biases approximates the matrix entries

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Objective

$$J = \sum_{i,j=1}^{|V|} (w_i^T c_j + b_i + b_j - \log X_{ij})^2$$

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Answer: Correct for this by adding an extra term that prevents this

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Objective

$$J = \sum_{i,j=1}^{|V|} f(X_{ij}) (w_i^T c_j + b_i + b_j - \log X_{ij})^2$$

f: A weighting function that assigns lower relative importance to frequent co-occurrences

GloVe: Global Vectors

Essentially a matrix factorization method

Does not compute standard SVD though

- 1. Re-weighting for frequency
- 2. Two-way factorization, unlike SVD which produces U, Σ, V
- 3. Bias terms

Final word embeddings for a word: The average of the word and the context vectors of that word

Summary

- We saw three different methods for training word embeddings
- Many, many, many variants and improvements exist
- Various tunable parameters/training choices:
 - Dimensionality of embeddings
 - Text for training the embeddings
 - The context window size, whether it should be symmetric
 - And the usual stuff: Learning algorithm to use, the loss function, hyper-parameters
- See references for more details