Word Embeddings

CS 6956: Deep Learning for NLP

THE UNIVERSITY OF UTAH

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

Context = previous words in sentence

- 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

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Continuous Bag of Words (CBOW)

Given a window of words of a length 2m + 1

- Call them: $x_{-m}, \cdots, x_{-1}\ x_0 x_1, \cdots, x_m$

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Train the model by minimizing loss over the dataset

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

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Need to define this to complete the model

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The CBOW model

- 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 $|V| \times n$

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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 $\mathcal{W}$

The CBOW loss: A worked example

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- Step 2: Their average:

$$\hat{v} = \frac{v_a + v_b + v_c + v_d}{4}$$

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  - Each element of this score corresponds to the score for a single word.

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- Step 4: the probability of a word being the center word

$$P(\cdot \mid a, b, d, e) = \text{softmax}(\mathcal{W}\hat{v})$$

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Note that this sum requires us to iterate over the entire vocabulary for each example!

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Skipgram

The other word2vec model

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Skipgram

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$$P(x_{context} \mid x_0)$$

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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 $x_{-m}, \cdots, x_{-1}, x_1, \cdots, x_m$
  - As before, these words correspond to one-hot vectors
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Remember the goal of learning: Make this probability highest for the observed words in this context.

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$$P(\, x_i = \cdot \mid x_0 = c\,) = \mathrm{softmax}(v)$$

Or more specifically:

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

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Negative sampling

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

This sum requires us to iterate over the entire vocabulary for each example!

- 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)

Negative sampling: The intuition

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  - That is, there are only k negatives for each positive example, instead of the entire vocabulary

We will visit negative sampling in the first homework

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 reading 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

Word2vec and matrix factorization

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

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Two key points to note:

Word2vec and matrix factorization

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Two key points to note:

1. The entries in the matrix are a shifted pointwise mutual information (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

Word2vec and matrix factorization

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

Word2vec and matrix factorization

[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

This lecture

- The word2vec models: CBOW and Skipgram
- Connection between word2vec and matrix factorization
- 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 i in the context of j

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

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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

The GloVe objective

Notation:

- i : word, j : a context word
- w_i: The word embedding for i
- c_j: The context embedding for j
- b_i^w, b_j^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 w_i, 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

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

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Problem: Pairs that frequently co-occur tend to dominate the objective.

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

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Objective

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

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 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