Word Embeddings: Beyond word2vec

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Overview

Topic: An overview of word embedding models and their properties

- What are word embeddings?
- Why are they so important?

Word Embeddings

Word embeddings: Mapping words (or more generally, entities from vocabularies) to vectors

- word2vec
- GloVe
- fastText
- StarSpace
- RAND-WALK
- ... and more

Why Word Embeddings?

Typical text representation: 1-hot encoding

Given a collection of texts with a vocabulary of size V, word i in the vocabulary is represented with V-dimensional vector with zeros everywhere, 1 in position i.
Problems:

- all words in the vocabulary have the same distance, given a distanse measure (eg cosine distance)
- We would like to use distance (or similarity) as a measure of semantic similarity
- Ideally, we would like a compact D-dimensional representation such that $D << V$

Word Analogies

Semantics as linear algebra

$$v(king) - v(man) + v(woman) \approx v(queen)$$

Distributional Hypothesis

'Words that occur in similar contexts tend to have similar meanings' Harris, 1954

'You shall know a word by the company it keeps'

Firth, 1957

Neural Language Models

Core idea: Approximate a Statistical Language Model with a neural network (Bengio et.al. 2003)
Statistical Language Model: Conditional Probability of the next word given the previous ones.

$$\hat{P}(w_i^T) = \prod_{i=1}^{T} \hat{P}(w_i | w_1^{t-1})$$

where w_i the i-th word and $w_i^j = (w_i, w_{i+1}, ..., w_{j-1}, w_j)$
Simplification (n-gram model):

$$\hat{P}(w_t | w_1^{t-1}) \approx P(w_t | w_{t-n+1}^{t-1})$$

Use a neural net to approximate the model (and also avoid assigning zero probability to sequences never appearing in a training corpus)

word2vec

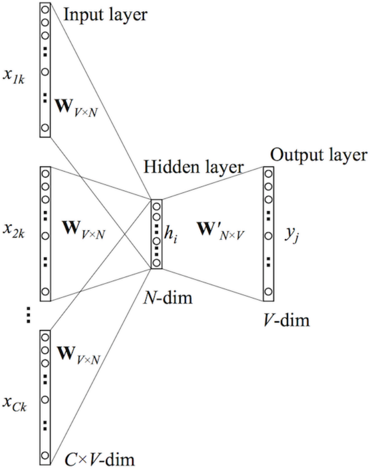
Fast forward 20 years later:
2013, Mikolov et. al. introduce word2vec. A very fast implementation of neural language models

- CBOW : Predict the word given context
- SkipGram: Predict context given word

Dealing with performance:

- negative sampling
- hierarchical softmax
- async SGD

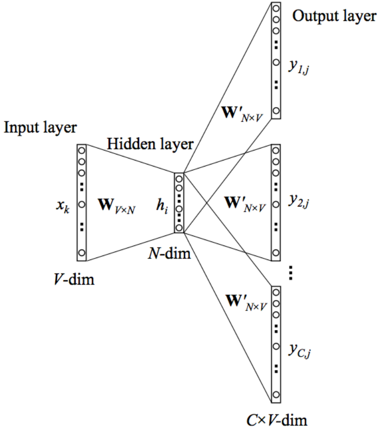
word2vec - CBOW



[1]

[1] Image Source: Wikipedia

word2vec - SkipGram



2

[2] Image Source: Wikipedia

GloVe

Matrix Factorization

2014, Pennington et.al. introduce GloVe (Global Vectors).
Given a corpus, build the co-occurrence matrix of the words in the vocabulary in a given context size.
Learning: Minimize the objective function

$$J = \sum_{i,j=1}^{V} f(X_{ij})\dot{(}w_i^T \tilde{w}_j + b_i + \tilde{b}_j - log(X_{ij}))^2$$

GloVe

GloVe notation

where

X the co-occurrence (usually symmetric) matrix

$w_i, \tilde{w}_j$ word vectors (left,right context)

$b_i, \tilde{b}_j$ bias for words i, j

$$f(x) = \begin{cases} (x/x_{max})^a, x < x_{max} \\ 1, \quad x \geq x_{max} \end{cases}$$

and finally, the embedding of the word i is defined as

$$e_i = w_i + \tilde{w}_i$$

$a = 3/4$, $x_{max} = 100$.

fastText

Bag of Tricks

- Logic similar to word2vec / SkipGram model
- Word $\rightarrow$ subword information $\rightarrow$ n-grams $\rightarrow$ embeddings for n-grams
- Word Embedding: average of the n-gram embeddings

StarSpace

Comparing entities

Optimisation objective:

$$J = \sum L^{batch}(sim(a, b), sim(a, b_1^-), ..., sim(a, b_n^-))$$

- Generator of positive pairs (a,b), from the set E^+
- Generator of negative entities b_j^- from the set E^- (negative sampling as in word2vec)
- sim: Similarity function (cosine similarity, dot product)
- L^{batch} comparison of the positive pair with the negative pairs. (hinge, softmax)

Bonus Round: RAND-WALK

A random walk over words

- A generative model
- Discourse direction vector c
- Choose words sampling $P[word\ emmited\ at\ time\ t] \propto exp(< w_i, c_i >)$

Objective functions

$$Jrw_1 = \sum_{w,w'} X_{ij}(log(X_{ij}) - ||u_w + u_{w'}||^2 - C)^2$$

$$Jrw_2 = \sum_{w,w'} X_{ij}(PMI(w, w') - \langle w, w' \rangle)^2$$

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

Features / Sentence Representation

Building features

Word embeddings and "traditional" ML, eg features for my SVM

- the average of n vectors
- average of the unit norm of the vectors [fastText]
- Smooth Inverse Frequency (SIF): First principal component of the weighted average of the vectors

C/C++ implementations

- word2vec : https://code.google.com/p/word2vec/
- GloVe : https://nlp.stanford.edu/projects/glove/
- fastText : https://github.com/facebookresearch/fastText
- StarSpace : https://github.com/facebookresearch/StarSpace
- RAND-WALK : TBA [work in progress]

Python

- gensim : https://radimrehurek.com/gensim/
- glove-python https://github.com/maciejkula/glove-python

Applications in NLP

Metaphor detection

- train (or download) an embedding model
- label metaphor and literal examples
- locate the verb in a sentence, get the context, average embeddings
- train a model with LogisticRegression or SVC

Automating Curation

- news stream: approved vs non-approved
- use pre-tagged articles, extract document embeddings
- feed to classifier

Pre-trained Embedding Layers

```
from keras.layers import Embedding

embedding_layer = Embedding(len(word_index) + 1,
                            EMBEDDING_DIM,
                            weights=[embedding_matrix],
                            input_length=MAX_SEQUENCE_LENGTH,
                            trainable=False)
```

Questions and properties

Interesting properties

- relation of word2vec with pairwise mutual information (PMI) [Levy et. al.]
- relatively small dimensions work better (500)
- See RAND-WALK [Arora et. al.]

References

- Efficient Estimation of Word Representations in Vector Space, Mikolov et. al. 2013
- GloVe: Global Vectors for Word Representation, Pennington et. al. 2014
- Bag of Tricks for Efficient Text Classification, Joulin, et. al. 2016
- StarSpace: Embed All The Things!, Joulin, et. al. 2017
- A Simple but Tough-to-Beat Baseline for Sentence Embeddings, Arora et. al. 2016
- RAND-WALK: A Latent Variable Model Approach to Word Embeddings, Arora et. al. 2017
- Neural Word Embedding as Implicit Matrix Factorization, Levy et. al. 2014

The End (and thanks!)