

Statistical Natural Language Processing

Distributed representations

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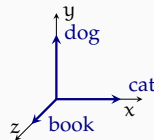
Representations of linguistic units

- Most ML methods we use depend on how we represent the objects of interest, such as
 - words, morphemes
 - sentences, phrases
 - letters, phonemes
 - documents
 - speakers, authors
 - ...
- The way we represent these objects interacts with the ML methods
- We will mostly talk about word representations
 - They are also applicable any of the above

Symbolic (one-hot) representations

A common way to represent words is one-hot vectors

$$\begin{aligned} \text{cat} &= (0, \dots, 1, 0, 0, \dots, 0) \\ \text{dog} &= (0, \dots, 0, 1, 0, \dots, 0) \\ \text{book} &= (0, \dots, 0, 0, 1, \dots, 0) \\ &\dots \end{aligned}$$

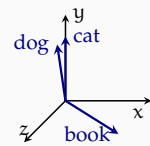


- No notion of similarity
- Large and sparse vectors

More useful vector representations

- The idea is to represent similar words with similar vectors

$$\begin{aligned} \text{cat} &= (0, 3, 1, \dots, 4) \\ \text{dog} &= (0, 3, 0, \dots, 3) \\ \text{book} &= (4, 1, 4, \dots, 5) \\ &\dots \end{aligned}$$



- The similarity between the vectors may represent similarities based on
 - syntactic
 - semantic
 - topical
 - form
 - ... features useful in a particular task

Where do the vector representations come from?

- The vectors are (almost certainly) learned from the data
- Typically using an unsupervised (or self-supervised) method
- The idea goes back to,

You shall know a word by the company it keeps. —Firth (1957)
- In practice, we make use of the contexts (company) of the words to determine their representations
- The words that appear in similar contexts are mapped to similar representations

How to calculate word vectors?

count word in context

$$\begin{array}{r} \text{cat} \\ \text{dog} \\ \text{book} \end{array} \begin{bmatrix} c_1 & c_2 & c_3 & \dots & c_m \\ 0 & 3 & 1 & \dots & 4 \\ 0 & 3 & 0 & \dots & 3 \\ 4 & 1 & 4 & \dots & 5 \end{bmatrix}$$

- + Now words that appear in the same contexts will have similar vectors
 - The frequencies are often normalized (PMI, TF-IDF)
 - The data is highly correlated: lots of redundant information
 - Still large and sparse

How to calculate word vectors?

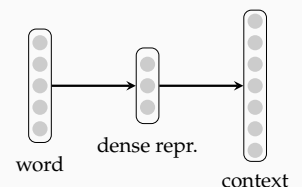
count, factorize, truncate

$$\begin{array}{r} w_1 \\ w_2 \\ w_3 \\ \dots \end{array} \begin{bmatrix} c_1 & c_2 & c_3 & \dots & c_m \\ 0 & 3 & 1 & \dots & 4 \\ 0 & 3 & 0 & \dots & 3 \\ 4 & 1 & 4 & \dots & 5 \\ \dots & \dots & \dots & \dots & \dots \end{bmatrix} = \begin{array}{r} z_1 & z_2 & z_3 & \dots & z_m \\ 1 & 5 & 9 & \dots & 4 \\ 1 & 4 & 1 & \dots & 3 \\ 9 & 1 & 1 & \dots & 5 \\ \dots & \dots & \dots & \dots & \dots \end{array} \begin{bmatrix} \sigma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_m \end{bmatrix} \begin{array}{r} c_1 & c_2 & c_3 & \dots & c_m \\ 0 & 3 & 1 & \dots & 4 \\ 0 & 3 & 0 & \dots & 3 \\ 9 & 1 & 8 & \dots & 0 \\ \dots & \dots & \dots & \dots & \dots \end{array} \begin{array}{r} u_1 \\ u_2 \\ u_3 \\ \dots \end{array}$$

How to calculate word vectors?

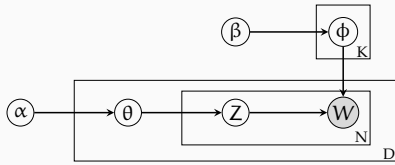
predict the context from the word, or word from the context

- The task is predicting
 - the context of the word from the word itself
 - or the word from its context
- Task itself is not interesting
- We are interested in the hidden layer representations learned



How to calculate word vectors?

latent variable models (e.g., LDA)



- Assume that the each 'document' is generated based on a mixture of latent variables
- Learn the probability distributions
- Typically used for *topic modeling*
- Can model words too (as a mixture of latent variables)

A toy example

A four-sentence corpus with *bag of words* (BOW) model.

The corpus:

- S1: She likes cats and dogs
- S2: He likes dogs and cats
- S3: She likes books
- S4: He reads books

Term-document (sentence) matrix

| | S1 | S2 | S3 | S4 |
|-------|----|----|----|----|
| she | 1 | 0 | 1 | 0 |
| he | 0 | 1 | 0 | 1 |
| likes | 1 | 1 | 1 | 0 |
| reads | 0 | 0 | 0 | 1 |
| cats | 1 | 1 | 0 | 0 |
| dogs | 1 | 1 | 0 | 0 |
| books | 0 | 0 | 1 | 1 |
| and | 1 | 1 | 0 | 0 |

A toy example

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The corpus:

- S1: She likes cats and dogs
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Term-term (left-context) matrix

| | # | she | he | likes | reads | cats | dogs | books | and |
|-------|---|-----|----|-------|-------|------|------|-------|-----|
| she | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| he | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| likes | 0 | 2 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| reads | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 0 | 0 |
| cats | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| dogs | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 | 1 |
| books | 0 | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| and | 0 | 0 | 0 | 0 | 0 | 1 | 1 | 0 | 0 |

Term-document matrices

- The rows are about the terms: similar terms appear in similar contexts
- The columns are about the context: similar contexts contain similar words
- The term-context matrices are typically sparse and large

Term-document (sentence) matrix

| | S1 | S2 | S3 | S4 |
|-------|----|----|----|----|
| she | 1 | 0 | 1 | 0 |
| he | 0 | 1 | 0 | 1 |
| likes | 1 | 1 | 1 | 0 |
| reads | 0 | 0 | 0 | 1 |
| cats | 1 | 1 | 0 | 0 |
| dogs | 1 | 1 | 0 | 0 |
| books | 0 | 0 | 1 | 1 |
| and | 1 | 1 | 0 | 0 |

SVD (again)

- Singular value decomposition is a well-known method in linear algebra
- An $n \times m$ (n terms m documents) term-document matrix X can be decomposed as

$$X = U \Sigma V^T$$

U is a $n \times r$ unitary matrix, where r is the rank of X ($r \leq \min(n, m)$). Columns of U are the eigenvectors of XX^T
 Σ is a $r \times r$ diagonal matrix of singular values (square root of eigenvalues of XX^T and $X^T X$)
 V^T is a $r \times m$ unitary matrix. Columns of V are the eigenvectors of $X^T X$

- One can consider U and V as PCA performed for reducing dimensionality of rows (terms) and columns (documents)

Truncated SVD

$$X = U \Sigma V^T$$

- Using eigenvectors (from U and V) that correspond to k largest singular values ($k < r$), allows reducing dimensionality of the data with minimum loss
- The approximation,

$$\hat{X} = U_k \Sigma_k V_k$$

results in the best approximation of X , such that $\|\hat{X} - X\|_F$ is minimum

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- Note that r and n may easily be millions (of words or contexts), while we choose k much smaller (a few hundreds)

Truncated SVD (2)

$$\begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,m} \\ x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,m} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,m} \\ x_{3,1} & x_{3,2} & x_{3,3} & \dots & x_{3,m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & x_{n,3} & \dots & x_{n,m} \end{bmatrix} =$$

$$\begin{bmatrix} u_{1,1} & \dots & u_{1,k} \\ u_{2,1} & \dots & u_{2,k} \\ u_{3,1} & \dots & u_{3,k} \\ \vdots & \ddots & \vdots \\ u_{n,1} & \dots & u_{n,k} \end{bmatrix} \times \begin{bmatrix} \sigma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_k \end{bmatrix} \times \begin{bmatrix} v_{1,1} & v_{1,2} & \dots & v_{1,m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{k,1} & v_{k,2} & \dots & v_{k,m} \end{bmatrix}$$

Truncated SVD (2)

$$\begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,m} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,m} \\ x_{3,1} & x_{3,2} & x_{3,3} & \dots & x_{3,m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & x_{n,3} & \dots & x_{n,m} \end{bmatrix} = \begin{bmatrix} u_{1,1} & \dots & u_{1,k} \\ u_{2,1} & \dots & u_{2,k} \\ u_{3,1} & \dots & u_{3,k} \\ \vdots & \ddots & \vdots \\ u_{n,1} & \dots & u_{n,k} \end{bmatrix} \times \begin{bmatrix} \sigma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_k \end{bmatrix} \times \begin{bmatrix} v_{1,1} & v_{1,2} & \dots & v_{1,m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{k,1} & v_{k,2} & \dots & v_{k,m} \end{bmatrix}$$

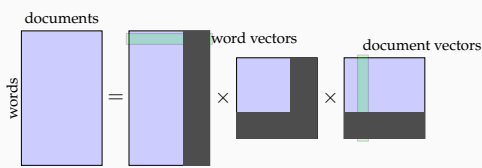
The term₁ can be represented using the first row of \mathbf{U}_k

Truncated SVD (2)

$$\begin{bmatrix} x_{1,1} & x_{1,2} & x_{1,3} & \dots & x_{1,m} \\ x_{2,1} & x_{2,2} & x_{2,3} & \dots & x_{2,m} \\ x_{3,1} & x_{3,2} & x_{3,3} & \dots & x_{3,m} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ x_{n,1} & x_{n,2} & x_{n,3} & \dots & x_{n,m} \end{bmatrix} = \begin{bmatrix} u_{1,1} & \dots & u_{1,k} \\ u_{2,1} & \dots & u_{2,k} \\ u_{3,1} & \dots & u_{3,k} \\ \vdots & \ddots & \vdots \\ u_{n,1} & \dots & u_{n,k} \end{bmatrix} \times \begin{bmatrix} \sigma_1 & \dots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \dots & \sigma_k \end{bmatrix} \times \begin{bmatrix} v_{1,1} & v_{1,2} & \dots & v_{1,m} \\ \vdots & \vdots & \ddots & \vdots \\ v_{k,1} & v_{k,2} & \dots & v_{k,m} \end{bmatrix}$$

The document₁ can be represented using the first column of \mathbf{V}_k^T

Truncated SVD: with a picture



- Step 1 Get word-context associations
- Step 2 Decompose
- Step 3 Truncate

Truncated SVD example

The corpus:

(S1) She likes cats and dogs
 (S2) He likes dogs and cats
 (S3) She likes books
 (S4) He reads books

| | S1 | S2 | S3 | S4 |
|-------|----|----|----|----|
| she | 1 | 0 | 1 | 0 |
| he | 0 | 1 | 0 | 1 |
| likes | 1 | 1 | 1 | 0 |
| reads | 0 | 0 | 0 | 1 |
| cats | 1 | 1 | 0 | 0 |
| dogs | 1 | 1 | 0 | 0 |
| books | 0 | 0 | 1 | 1 |
| and | 1 | 1 | 0 | 0 |

Truncated SVD (k = 2)

$$\mathbf{U} = \begin{bmatrix} -0.30 & 0.28 \\ -0.24 & -0.63 \\ -0.52 & 0.15 \\ -0.03 & -0.49 \\ -0.43 & 0.01 \\ -0.43 & 0.01 \\ -0.03 & -0.49 \\ -0.43 & 0.01 \end{bmatrix} \begin{matrix} \text{she} \\ \text{he} \\ \text{likes} \\ \text{reads} \\ \text{cats} \\ \text{dogs} \\ \text{books} \\ \text{and} \end{matrix}$$

$$\Sigma = \begin{bmatrix} 3.11 & 0 \\ 0 & 1.81 \end{bmatrix}$$

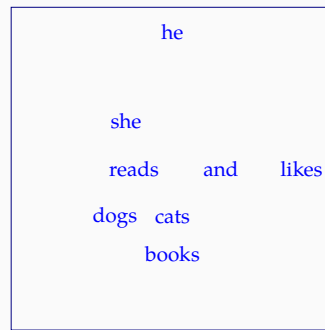
$$\mathbf{V}^T = \begin{bmatrix} -0.68 & 0.26 & -0.11 & -0.66 \\ -0.66 & -0.23 & 0.48 & 0.50 \end{bmatrix} \begin{matrix} S1 & S2 & S3 & S4 \end{matrix}$$

Truncated SVD (with BOW sentence context)



The corpus:
 (S1) She likes cats and dogs
 (S2) He likes dogs and cats
 (S3) She likes books
 (S4) He reads books

Truncated SVD (with single word context)



The corpus:
 (S1) She likes cats and dogs
 (S2) He likes dogs and cats
 (S3) She likes books
 (S4) He reads books

SVD: LSI/LSA

- SVD applied to term-document matrices are called
- *Latent semantic analysis (LSA)* if the aim is constructing *term* vectors
 - Semantically similar words are closer to each other in the vector space
 - *Latent semantic indexing (LSI)* if the aim is constructing *document* vectors
 - Topically related documents are closer to each other in the vector space

Context matters

- In SVD (and other) vector representations, the choice of context matters
- Larger contexts tend to find semantic/topical relationships
 - Smaller (also order-sensitive) contexts tend to find syntactic generalizations

SVD based vectors: practical concerns

- In practice, instead of raw counts of terms within contexts, the term-document matrices typically contain
 - pointwise mutual information
 - tf-idf
- If the aim is finding latent (semantic) topics, frequent/syntactic words (*stopwords*) are often removed
- Depending on the measure used, it may also be important to normalize for the document length

SVD-based vectors: applications

- The SVD-based methods is commonly used in information retrieval
 - The system builds document vectors using SVD
 - The search terms are also considered as a 'document'
 - System retrieves the documents whose vectors are similar to the search term
- The well known Google *PageRank* algorithm is a variation of the SVD

In this context, the results is popularly called "the \$25 000 000 000 eigenvector".

SVD-based vectors: applications

- The SVD-based methods for semantic similarity is also common
- It was shown that the vector space models outperform humans in
 - TOEFL synonym questions
Receptors for the sense of smell are located at the top of the nasal cavity.
A. upper end **B.** inner edge **C.** mouth **D.** division
 - SAT analogy questions
Paltry is to significance as _____ is to _____.
A. redundant : discussion
B. austere : landscape
C. opulent : wealth
D. oblique : familiarity
E. banal : originality
- In general the SVD is a very important method in many fields

the song

Predictive models

- Instead of dimensionality reduction through SVD, we try to predict
 - either the target word from the context
 - or the context given the target word
- We assign each word to a fixed-size random vector
- We use a standard ML model and try to reduce the prediction error with a method like gradient descent
- During learning, the algorithm optimizes the vectors as well as the model parameters
- In this context, the word-vectors are called **embeddings**
- This types of models has been very popular during last few years

Predictive models

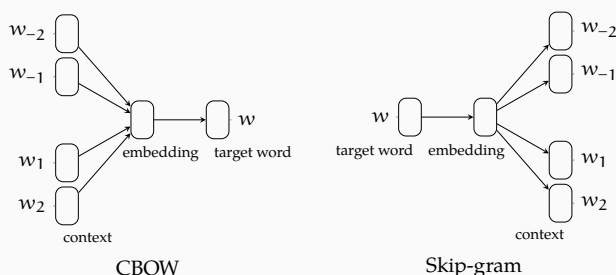
- The idea is the 'locally' predict the context a particular word occurs
- Both the context and the words are represented as low dimensional dense vectors
- Typically, neural networks are used for the prediction
- The hidden layer representations are the vectors we are interested

word2vec

- word2vec** is a popular algorithm and open source application for training word vectors (Mikolov et al. 2013)
- It has two modes of operation
 - CBOW** or continuous bag of words predict the word using a window around the word
 - Skip-gram** does the reverse, it predicts the words in the context of the target word using the target word as the predictor

word2vec

CBOW and skip-gram modes – conceptually



word2vec

a bit more in detail

- For each word w algorithm learns two sets of embeddings
 - v_w for words
 - c_w for contexts
- Objective of the learning is to maximize (skip-gram)

$$P(c | w) = \frac{e^{v_w \cdot c_c}}{\sum_{c' \in c} e^{c' \cdot v_w}}$$

Note that the above is simply *softmax* – the learning method is equivalent to logistic regression

- Now, we can use gradient-based approaches to find word and context vectors that maximize this objective

Issues with softmax

$$P(c | w) = \frac{e^{v_w \cdot c_c}}{\sum_{c' \in \mathcal{C}} e^{c' \cdot v_w}}$$

- A particular problem with models with a softmax output is high computational cost:
 - For each instance in the training data denominator need to be calculated over the whole vocabulary (can easily be millions)
- Two workarounds exist:
 - *Negative sampling*: a limited number of negative examples (sampled from the corpus) are used to calculate the denominator
 - *Hierarchical softmax*: turn output layer to a binary tree, where probability of a word equals to the probability of the path followed to find the word
- Both methods are applicable to training, during prediction, we still need to compute the full softmax

word2vec: some notes

- Note that word2vec is not 'deep'
- word2vec performs well, and it is much faster than earlier (more complex) ANN architectures developed for this task
- The resulting vectors used by many (deep) ANN models, but they can also be used by other 'traditional' methods
- word2vec treats the context as a BoW, hence vectors capture semantic relationships
- There are many alternative formulations

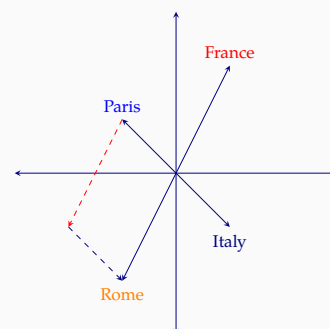
GloVe

- GloVe is another popular method for obtaining word vectors (Pennington, Socher, and Manning 2014)
- It tries to combine intuitions from both SVD-like 'counting' methods, and prediction-based methods
- It is reported performs better on smaller data sets

Word vectors and syntactic/semantic relations

Word vectors map some syntactic/semantic relations to vector operations

- Paris - France + Italy = Rome
- king - man + woman = queen
- ducks - duck + mouse = mice



Using vector representations

- Dense vector representations are useful for many ML methods
- They are particularly suitable for neural network models
- 'General purpose' vectors can be trained on unlabeled data
- They can also be trained for a particular purpose, resulting in 'task specific' vectors
- Dense vector representations are not specific to words, they can be obtained and used for any (linguistic) object of interest

Evaluating vector representations

- Like other unsupervised methods, there are no 'correct' labels
- Evaluation can be based on
 - Intrinsic evaluation based on success on finding analogy/synonymy
 - Extrinsic evaluation, based on whether they improve a particular task (e.g., parsing, sentiment analysis) or not
 - Correlation with human judgments

Differences of the methods

...or the lack thereof

- It is often claimed, after excitement created by word2vec, that prediction-based models work better
- Careful analyses suggest, however, that word2vec can be seen as an approximation to a special case of SVD
- Performance differences seem to boil down to how well the hyperparameters are optimized
- In practice, the computational requirements is probably a bigger factor in choice

Summary

- Dense vector representations of linguistic units (as opposed to symbolic representations) allow calculating similarity/difference between the units
- They can be either based on counting (SVD), or predicting (word2vec, GloVe)
- They are particularly suitable for ANNs, deep learning architectures

Next:

Mon Text classification

Fri Q&A, other NLP applications (?)

Additional reading, references, credits

- Upcoming edition of the textbook (Jurafsky and Martin 2009, ch.15 and ch.16) has two chapters covering the related material.
- See Levy, Goldberg, and Dagan (2015) for a comparison of different ways of obtaining embeddings.