Deep Learning for Natural Language Processing

More training methods for word embeddings

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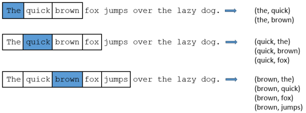
overview

- while SGNS is probably the most well-known algorithm for training word embedding models, there are several others
- we'll take a quick tour of some of the most prominent
  - "**prediction-based**": collecting training instances from individual occurrences (like SGNS)



  - "**count-based**": methods based on co-occurrence matrices

$$
X = \begin{array}{c} \\ \textit{I} \\ \textit{like} \\ \textit{enjoy} \\ \textit{deep} \\ \textit{learning} \\ \textit{NLP} \\ \textit{flying} \\ . \end{array}
\begin{array}{c}
\begin{array}{cccccccc} \textit{I} & \textit{like} & \textit{enjoy} & \textit{deep} & \textit{learning} & \textit{NLP} & \textit{flying} & . \end{array} \\
\begin{bmatrix}
0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\
2 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\
1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\
0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\
0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\
0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\
0 & 0 & 0 & 0 & 1 & 1 & 1 & 0
\end{bmatrix}
\end{array}
$$

continuous bag-of-words for training embeddings

- the continuous bag-of-words (CBoW) model considers the **whole context** instead of breaking it up into separate pairs:

*the quick brown **fox** jumps over the lazy dog*

$\Downarrow$

{ *the, quick, brown, jumps, over, the* }, ***fox***

- the model is almost like SGNS:

$$P(\text{true pair}|(w, C)) = \frac{1}{1 + \exp\left(-V_T(w) \cdot V_C(C)\right)}$$

where $V'(C)$ is the sum of context embeddings

$$V_C(C) = \sum_{c \in C} V_C(c)$$

- also available in the `word2vec` software

how can we deal with **out-of-vocabulary** words?

- what if *dingo* is in the vocabulary but not *dingoes*?
- humans can handle these kinds of situations!
- **fastText** (Bojanowski et al., 2017) modifies the SGNS model to handle these situations:

$$V_T(w) = \sum_{g \in \mathcal{G}} \boldsymbol{z}_g$$

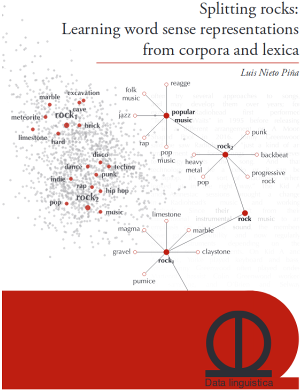
where $\mathcal{G}$ is the set of subwords for w:

$$\mathcal{G} = \{\text{'<dingoes>', '<di', 'din', 'ing', ..., 'ngoes>'}\}$$

- handles rare words and OOV words better than SGNS

how can we deal with **multiple senses**?

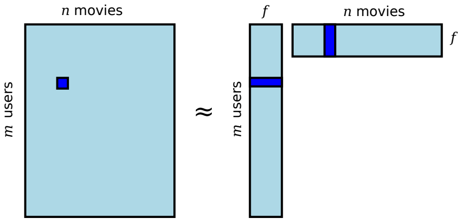
- for instance, ***rock*** can refer to a stone or a type of music

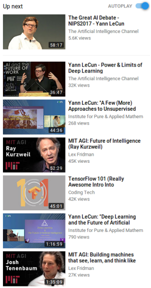


- Luis's PhD thesis from a few weeks back: *Splitting rocks: Learning word sense representations from corpora and lexica*

compare: matrix factorization in recommender systems

- the most famous approach in recommenders is based on **factorization** of the user/item rating matrix





- to predict a missing cell (rating of an unseen item):

$$\hat{r}_{ui} = \boldsymbol{p}_u \cdot \boldsymbol{q}_i$$

where $\boldsymbol{p}_u$ is the user's vector, and $\boldsymbol{q}_i$ the item's vector

example of a word–word co-occurrence matrix

- assume we have the following set of texts:
  - “I like NLP”
  - “I like deep learning”
  - “I enjoy flying”

$$X = \begin{array}{c} \\ I \\ like \\ enjoy \\ deep \\ learning \\ NLP \\ flying \\ . \end{array} \begin{array}{c} \begin{array}{cccccccc} I & like & enjoy & deep & learning & NLP & flying & . \end{array} \\ \begin{bmatrix} 0 & 2 & 1 & 0 & 0 & 0 & 0 & 0 \\ 2 & 0 & 0 & 1 & 0 & 1 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 1 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 & 0 & 0 & 1 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 & 1 & 1 & 0 \end{bmatrix} \end{array}$$

[source]

matrix-based word embeddings

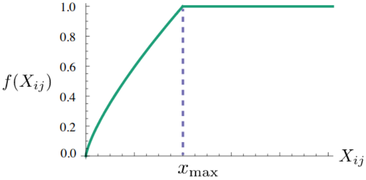
- **Latent Semantic Analysis** (Landauer and Dumais, 1997) was the first vector-based word representation model
  - it applies singular value decomposition (SVD) to a word–document matrix
- several other approaches:
  - different types of matrices (word–document, word–word, . . .)
  - transformations of the matrix (log, PMI, . . .)
  - different types of factorizations (none, SVD, NMF, . . .)
- Levy and Goldberg (2014) show a connection between SGNS and matrix-based methods

GloVe

- GloVe (Pennington et al., 2014) is a famous matrix-based method
  - https://nlp.stanford.edu/projects/glove/
- they try to find word and context vectors to satisfy

$$V_T(w) \cdot V_C(c) + b_T(w) + b_C(c) = \log \#(w, c)$$

- they downweight infrequent words



what should we prefer, count-based or prediction-based?

- see Baroni et al. (2014) for a comparison of count-based and prediction-based
  - they come out strongly in favor of prediction-based
  - but this result has been questioned
- pros and cons:
  - prediction-based methods are sensitive to the order the examples are processed
  - count-based methods can be messy to implement with a large vocabulary

references I

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