Word2Vec

Lexical Resources

October 21st, 2020

Outline

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- Word embeddings are context-based vector representation of words used in machine learning, whereas DS is a semantic theory of meaning, which generally employs vectors to represent meanings.
- Word2vec is a word embedding algorithm that was presented in three papers: Mikolov, Yih, and Zweig (2013) and Mikolov et al. (2013b,a)

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Why does word2vec matter?

Word embeddings in general, and word2vec in particular are widely used in descriptive & theoretical linguistics

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- has been shown to describe a latent code
- highlights how to combine various nifty tricks from the machine learning community

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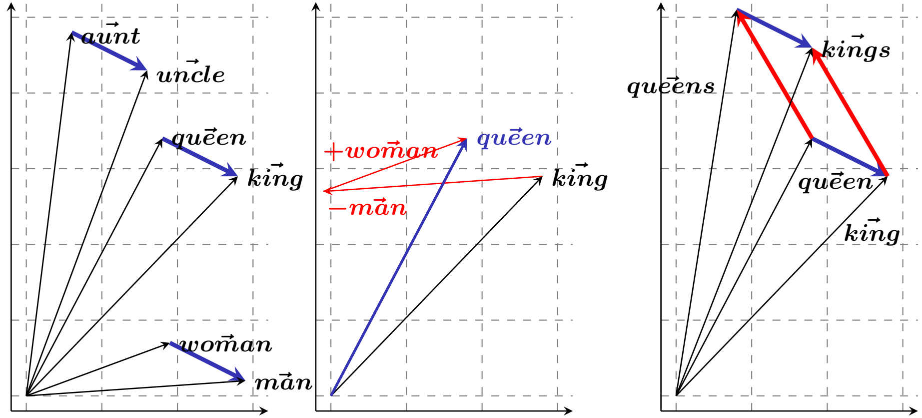

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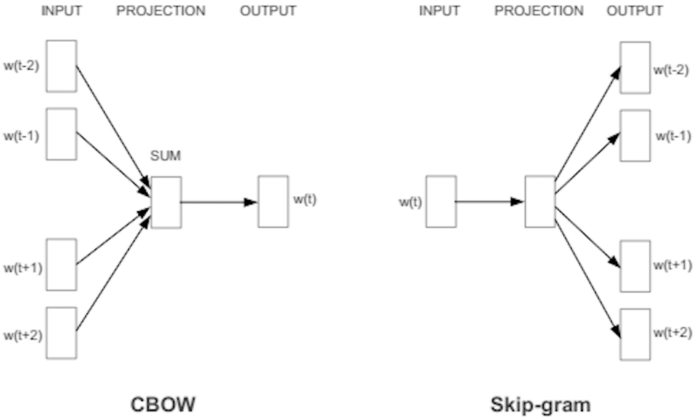
Technical Definition

word2vec comprises 2 architectures

- CBOW uses the context of a word as the input, and tries to predict the word
- Skip-gram uses a word as an input, and tries to predict each word in its context.



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CBOW architecture

- CBOW is comprised of one linear projection $\boldsymbol{W_P} = [V \times D]$ and a log-linear classifier $\boldsymbol{W_C} = [D \times V]$
  NB: V is the size of the vocabulary and D is the number of dimensions.

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Cbow architecture

- Cbow is comprised of one linear projection $\boldsymbol{W_P} = [V \times D]$ and a log-linear classifier $\boldsymbol{W_C} = [D \times V]$
  NB: V is the size of the vocabulary and D is the number of dimensions.

- All context words are first transformed as one-hot vectors, then down-projected in a vector space R^D using the projection $\boldsymbol{W_P}$. The average of all projected vectors is then used as input for the log-linear classifier $\boldsymbol{W_C}$ itself.

$$\vec{h_i} = \frac{1}{2t}\left(\sum_{j=i-1-t}^{i-1} \boldsymbol{W_P} \cdot \vec{w_j} + \sum_{j=i+1}^{i+1+t} \boldsymbol{W_P} \cdot \vec{w_j} \right)$$

$$\hat{y_i} = \mathrm{softmax}(\boldsymbol{W_C} \cdot \vec{h_i})$$

NB: The above corresponds to a context *window* of size t around the target word

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- Given a word w_i, and its index i in the vocabulary, we define

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- The classifier $\boldsymbol{W_C}$ only serves for training, and is to be discarded afterwards.

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  where ${\boldsymbol{W_C}}^j$ is the j^{th} column vector of the matrix $\boldsymbol{W_C}$. The components of $\hat{y}$ sum to 1, and therefore define a probability distribution for each element of our vocabulary ($\hat{y}$ is a vector of dimension V).

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- maximizing the probability of predicting the current word knowing the context is equivalent to minimizing the negative log-likelihood for that word.

$$\mathcal{L}(\hat{y}, w_i) = -\log \hat{y}_i$$

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- Like with CBOW, we derive vectors from the $\boldsymbol{W_P}$ matrix
- A probability distribution is inferred by applying a softmax after the classifier's output.

$$\vec{h_i} = \boldsymbol{W_P} \cdot \vec{w_i}$$

$$\hat{y_i} = \text{softmax}(\boldsymbol{W_C} \cdot \vec{h_i})$$

where $\vec{w_i}$ is the one-hot vector for word w_i.

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- As all context words are to be predicted using the same input word, we aim to maximize the joint probability of all context words knowing the current word.

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- So the model is trained by minimizing the joint negative log-likelihood of each context word.

$$\mathcal{L}(\hat{y}, \langle w_{i-t}, \ldots, w_{i+t} \rangle) = -\left(\sum_{j=i-t}^{i-1} \log \hat{y}_j + \sum_{j=i+1}^{i+t} \log \hat{y}_j \right)$$

NB: In practice, the loss is averaged over the full input sentence.

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- Let D^+ the set of all pairs of words w and contexts c that occurs in our dataset, and let D^- a set of *negative examples* (also pairs of words and contexts), such that $D^+ \cap D^- = \emptyset$. Let $p(X = 1|w, c)$ the probability that $\langle w,\ c \rangle \in D^+$.

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- Minimizing $p(X = 1|w, c)$ is equivalent to maximizing $1 - p(X = 1|w, c)$.
- The objective is therefore to maximize

$$\prod_{\langle w,\ c\rangle \in D^+} p(X = 1|w, c) \prod_{\langle w,\ c\rangle \in D^-} \big(1 - p(X = 1|w, c)\big)$$

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Negative sampling—adapting the architecture

- We have to amend the network's architecture. We don't need a full distribution over the vocabulary, so we can replace the softmax function with a sigmoid: $\sigma(y) = \frac{1}{1+\exp(-y)}$. Vector representations for words and contexts still have to be drawn from two different matrices.

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- We therefore compute the score for $\langle w_j,\ w_i \rangle$ simply using $\sigma\big(\boldsymbol{W_C}^j \cdot (\boldsymbol{W_P} w_i)\big)$ for pairs drawn from D^+, and $\sigma\big(-\boldsymbol{W_C}^j \cdot (\boldsymbol{W_P} w_i)\big)$ for pairs drawn from D^-, as $1 - \sigma(y) = \sigma(-y)$

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- To limit computation complexity, we estimate the second term using only k negative examples.
- To obtain the loss function, we replace the negative likelihood of predicting word w_j knowing word w_i from previous loss functions.

$$-\log p(w_j|w_i) = -\log \sigma\big(\boldsymbol{W_C}^j \cdot (\boldsymbol{W_P} w_i)\big) + \sum_{w_n \in N} \sigma\big(-\boldsymbol{W_C}^n \cdot (\boldsymbol{W_P} w_i)\big)$$

where N is a set of k negative examples sampled for w_i.

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Hierarchical softmax & subsampling

- *Alternatively* to negative sampling, we can use a a **hierarchical softmax** and encode probabilities using a binary tree structure. Leaves correspond to words in the vocabulary, and each node n stores the relative probabilities of its children using a dedicated weight vector $\vec{v_n}$.

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$$p(w_j|\vec{h_i}) = \prod_{n \in \mathcal{P}(w_j)} \sigma\left(\vec{v_n} \cdot \vec{h_i}\right)$$

- Mikolov & al also proposed to avoid issues arising with class imbalance ("Zipf's law") by dropping words from the training set based on their frequency. They define the "**subsampling**" rate:

$$P(w_i) = 1 - \sqrt{\frac{t}{f(w_i)}}$$

where t is an hyperparameter (typically 10^{-5}) and $f(w)$ is the frequency of word w.

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- There are technical limitations: e.g., rare words have unreliable vectors, rare phenomena may not be consistently modeled
- Harris (1954), who put forward the idea of distributional structures, did not equate them with **meaning**:

> *To the extent that formal (distributional) structure can be discovered in discourse, it correlates in some way with the substance of what is being said [...] However, this is not the same thing as saying that the distributional structure of language (phonology, morphology, and at most a small amount of discourse structure) conforms in some one-to-one way with some independently discoverable structure of meaning.*

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- Bonami and Paperno (2018) test whether this assumption is consistent with distributional semantics

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  - *sell–seller*, but *dine–diner* or *see–seer*:
    knowing the meaning of the former does **not** entail knowing the meaning of the latter
- Bonami and Paperno (2018) test whether this assumption is consistent with distributional semantics
- Assuming it is, we would expect linear offsets for inflectional relations (e.g., $b\vec{are} - 3^{r\vec{d}}sg$) to be more consistent than those for derivational relations (e.g., $v\vec{er}b - ag\vec{e}nt$)

Word2vec in linguistics

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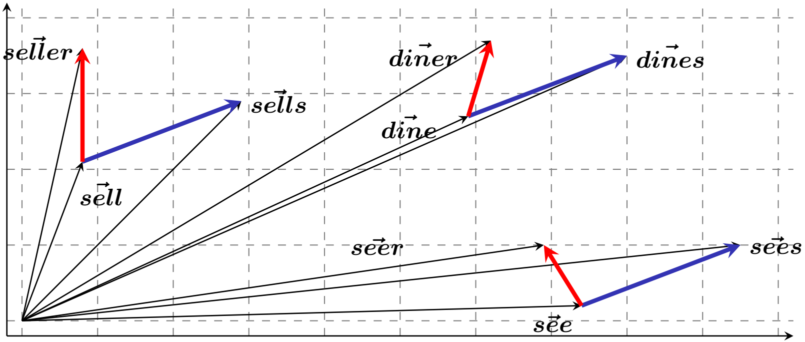

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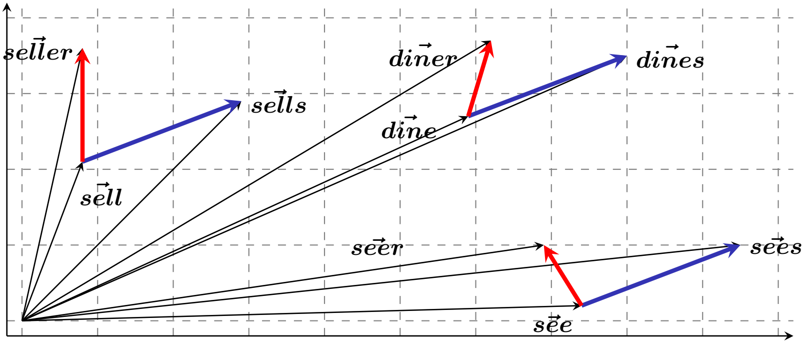

- They find that derivational relations yield significantly more variation than inflectional ones: derivational pairs stray more from the average value than inflectional pairs.

Word2vec in linguistics

Exercise

Let's imitate the experiment of Bonami and Paperno (2018)

1. Retrieve embeddings from `http://vectors.nlpl.eu/repository/20/6.zip`
2. Retrieve the CSV document containing agent–verb–3$^{\text{rd}}$ sg. triples for this exercise from `https://github.com/TimotheeMickus/lexres-2020/blob/main/lecture-4/triples.csv`.
3. Load the embeddings for all words in the CSV.
4. For each row, compute the offsets (i.e., the vector difference):
   4.1 compute the offsets between agent noun and bare verb
   4.2 compute the offsets between bare verb and 3$^{\text{rd}}$ sg. form
5. Compute the **average** offset between agent and verb (using the offsets from step 4.1), and the **average** offset between verb and 3$^{\text{rd}}$ sg. (using the offsets from step 4.2)
6. For each offset, compute its Euclidean distance to the average offset.
   NB: You now have two series of measurements, representing how your sample varies with respect to the average value.
7. Take the two comparable series of measurements you got from step 6, and compute a paired t-test (e.g. using the function `scipy.stats.ttest_rel`). What can you conclude?
8. Repeat steps 6 and 7, this time using cosine distance (i.e., $1 - \cos(\vec{u}, \vec{v})$)

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- NLPL's repository containing many pre-trained word2vec models (as well as other embeddings) for multiple languages: `http://vectors.nlpl.eu/repository/`

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