Deep Learning

14 Word Embeddings

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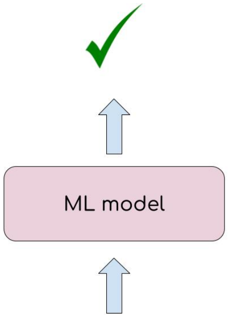
Why Word Embeddings?



IITH has been consistently ranked in the top 10 institutes in India for Engineering according to NIRF making it one of the most coveted schools for science and technology in the country.

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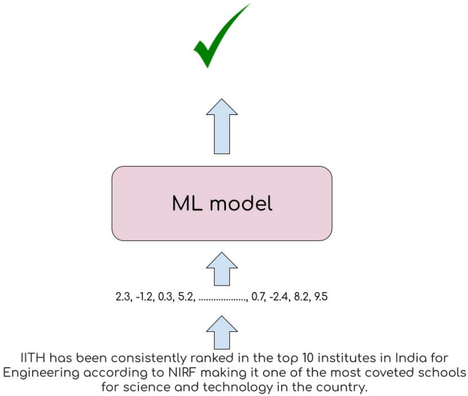

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3. Target: Representation for every word in V

One-hot Encoding

1. $|V|$ words encoded as binary vectors of length $|V|$

Dictionary	Word Representation					
A	1	0	0	....	0	0
Bus	0	1	0	....	0	0
Cat	0	0	1	....	0	0
⋮						
Tide	0	0	0	....	1	0
Zone	0	0	0	....	0	1

One-hot encoding: Drawbacks

1. Space inefficient (e.g. 13M words in Google 1T corpus)

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2. No notion of similarity (or, distance) between words

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3. Context can be defined as a 'h' word neighborhood
4. Each row (column): vectorial representation of the word (context)

Co-occurrence matrix

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

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3. Solution:Dimensionality reduction (SVD)!

SVD on the Co-occurrence matrix

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

SVD on the Co-occurrence matrix

भारतीय प्रौद्योगिकी संस्थान हैदराबाद
Indian Institute of Technology Hyderabad

1. $X = U\Sigma V^T$
2. $$\begin{bmatrix} & & \\ & X & \\ & & \end{bmatrix}_{m \times n} =$$
$$\begin{bmatrix} \uparrow & \cdots & \uparrow \\ u_1 & \cdots & u_k \\ \downarrow & \cdots & \downarrow \end{bmatrix}_{m \times k} \cdot \begin{bmatrix} \sigma_1 & & \\ & \ddots & \\ & & \sigma_k \end{bmatrix}_{k \times k} \cdot \begin{bmatrix} \leftarrow & v_1^T & \rightarrow \\ & \vdots & \\ \leftarrow & v_k^T & \rightarrow \end{bmatrix}_{k \times n}$$

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3. $X = \sigma_1 u_1 v_1^T + \sigma_2 u_2 v_2^T + \ldots + \sigma_k u_k v_k^T$
4. $\hat{X} = \sum_{i=1}^{d<k} \sigma_i u_i v_i^T$ is a d-rank approximation of X

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2. How do we reduce the representation size with SVD ?
3. $W_{\text{word}} = U_{m \times k} \cdot \Sigma_{k \times k}$

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2. Lesser dimensions but the same similarities! (one may verify that $XX^T = \hat{X}\hat{X}^T$)
3. $W_{\text{context}} = V \in \mathbb{R}^{n \times k}$ are taken as the representations for the context words

Count-based vs prediction-based models

1. Techniques we have seen so far rely on the counts (or, co-occurrence of words)

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2. Next, we see prediction based models for word embeddings

Word2Vec

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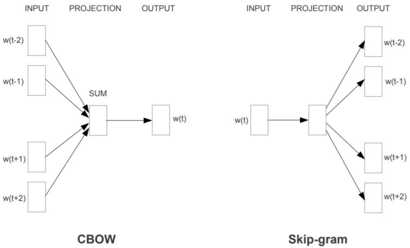
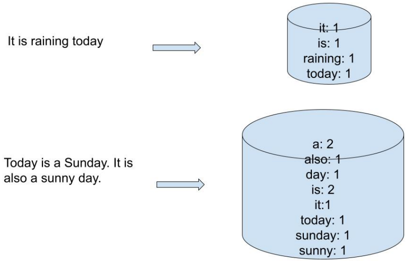
2. Predict words from the context
3. Two versions: Continuous Bag of Words (CBoW) and Skip-gram



Caption

Bag of Words (BoW)

1. Bag of Words: Collection and frequency of words



CBoW

1. Considers the embeddings of ‘h’ words before and ‘h’ words after the target word

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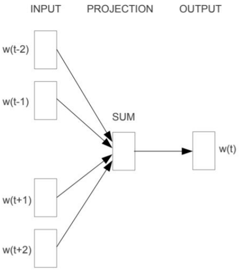
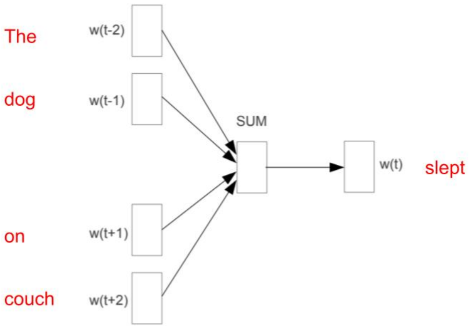
2. Adds them (order is lost) for predicting the target word



CBOW

CBoW

The dog slept on couch



CBow

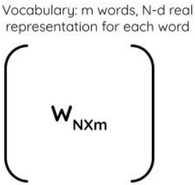
1. Size of the vocabulary $= m$

Vocabulary: m words, N-d real
representation for each word

$$\begin{bmatrix} W_{NXm} \end{bmatrix}$$

CBow

1. Size of the vocabulary $= m$
2. Dimension of the embeddings $= N$



Word Embeddings: CBoW

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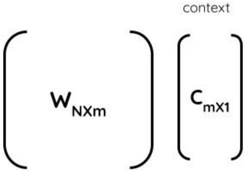
2. Representations of all the $(2h)$ words in the context are summed (result is an V-d context vector)



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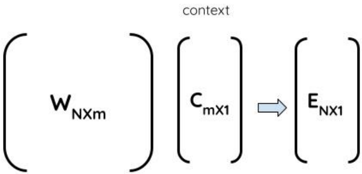

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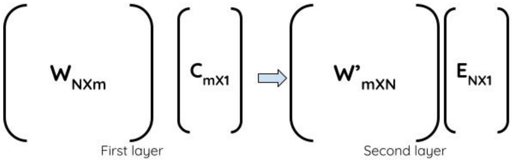

Word Embeddings: CBoW

1. Next layer has a weight matrix $W'_{V\times N}$
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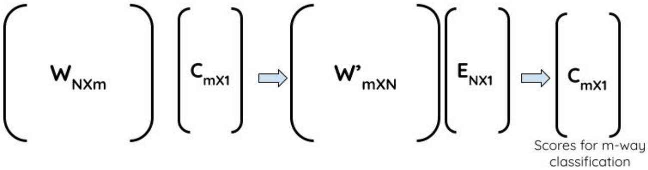
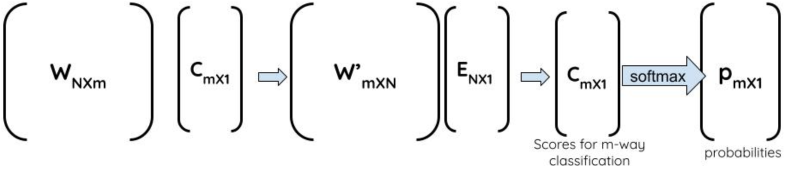


Word Embeddings: CBoW

1. V- way classification $\rightarrow$ (after a softmax) maximizes the probability for the target word



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1. $W_{N \times m}$ is the W_{context}
2. $W'_{V \times m}$ is the W_{words}