Deep Learning

14 Word Embeddings

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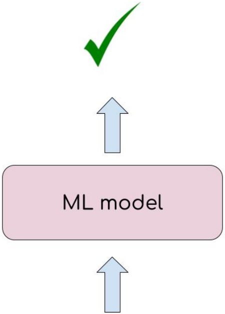
Jan-May 2023

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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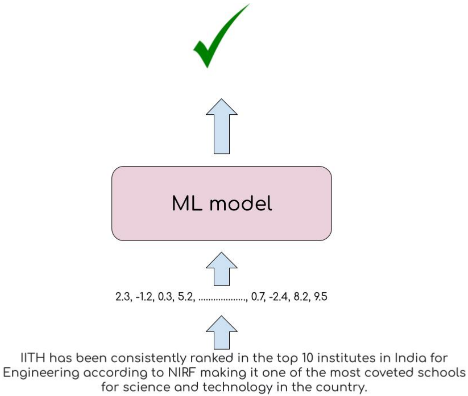

Terminology

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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

Distributed Representations

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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)!

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

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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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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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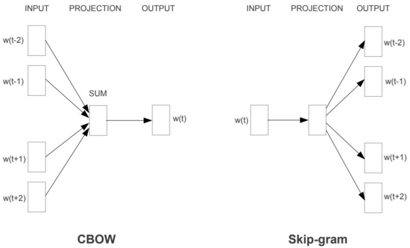
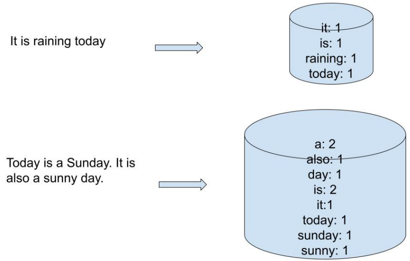
3. Two versions: Continuous Bag of Words (CBoW) and Skip-gram



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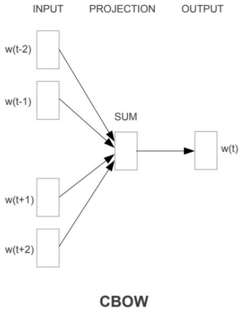
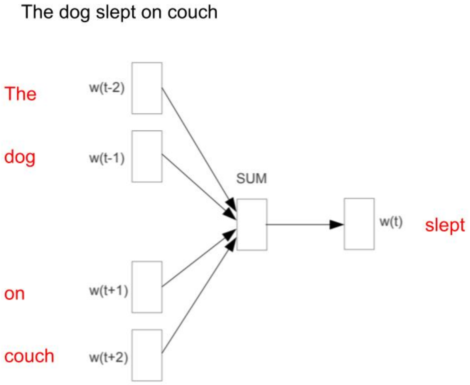
2. Adds them (order is lost) for predicting the target word



CBoW


The dog slept on couch
The
w(t-2)
dog
w(t-1)
SUM
w(t)
slept
on
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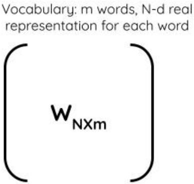
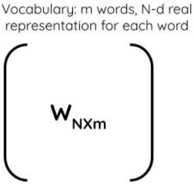


CBow

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



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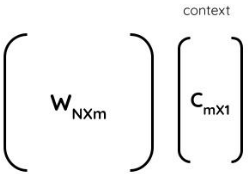
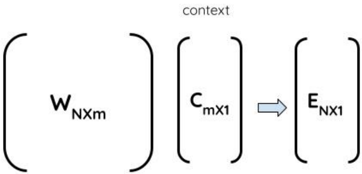


Word Embeddings: CBoW

1. Input layer $W_{N \times m}$ projects the context in to N-d space
2. Representations of all the $(2h)$ words in the context are summed (context is an V-d vector)



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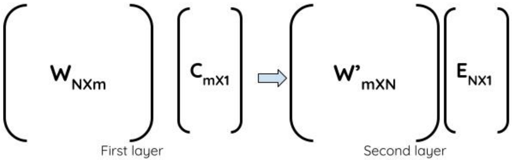

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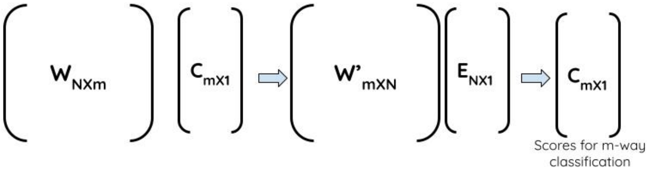
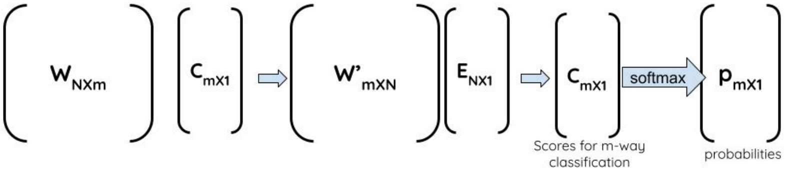


Word Embeddings: CBoW

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



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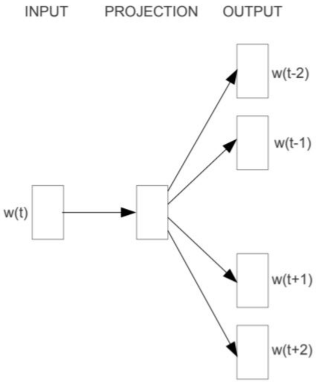
CBoW: issues

1. Softmax at the o/p is very expensive $\hat{y}_w = \frac{exp(u_c \cdot v_w)}{\sum_{w' \in V} exp(u_c \cdot v_{w'})}$

Word Embeddings: Skip-gram



Skip-gram

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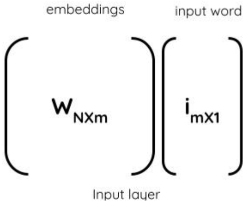

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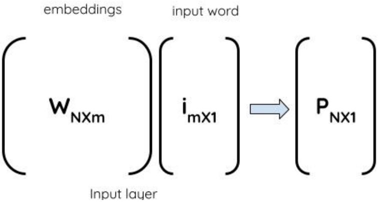

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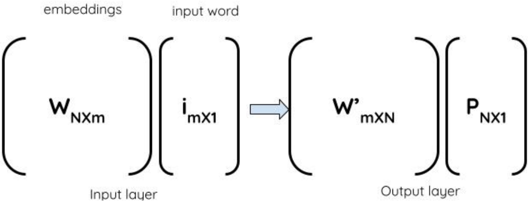

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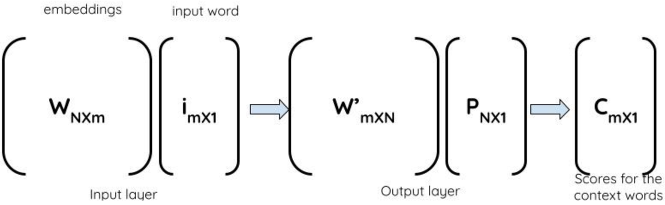

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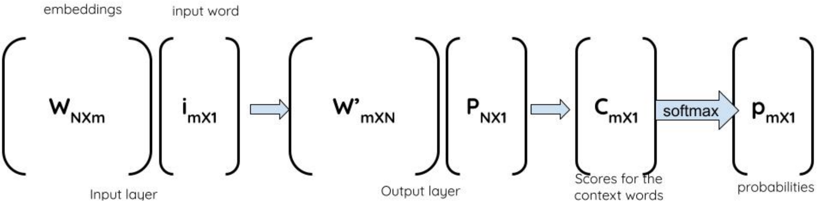

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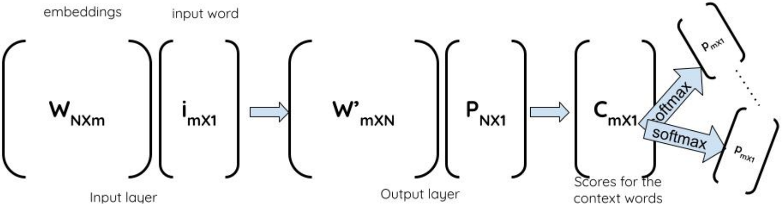

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Indian Institute of Technology Hyderabad

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2. Negative sampling: subset of incorrect words participate (instead of all)
3. Other solutions: Contrastive estimation, and hierarchical softmax

Glove

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2. Combines the score based and predict based approaches

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4. $\sum_{i,j}\left(v_i^T v_j + b_i + b_j - \log X_{ij}\right)^2$

Evaluating the embeddings

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3. Analogy

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2. Some studies favor the predict-based, some the cooccurrence based!!