Deep Learning

13 Word Embeddings

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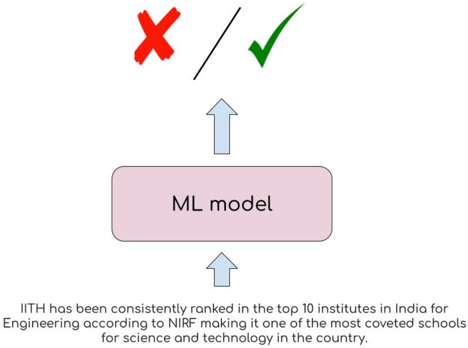
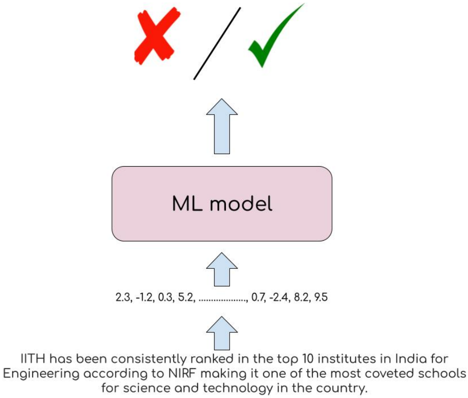
Why Word Embeddings?



Why Word Embeddings?



Terminology

- Corpus: a collection of authentic text organized into dataset

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- Vocabulary (V): Set of allowed words

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- Vocabulary (V): Set of allowed words
- Target: Representation for every word in V

One-hot Encoding

- Representation using discrete symbols

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- $|V|$ 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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One-hot encoding: Drawbacks

1. Space inefficient (e.g. 13M words in Google 1T corpus)
2. No notion of similarity (or, distance) between words
   - 'Dog' is as close to 'Cat' as it is to 'Machine'

Notion of Meaning for words

1. What is a good notion of meaning for a word?

Notion of Meaning for words

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2. How do we, humans, know the meaning of a word?

Notion of Meaning for words

1. What does silla mean?

Notion of Meaning for words

1. Let's see how this word is used in different contexts

   1. The $\boxed{\text{silla}}$ is by the window, offering a nice view of the garden.
   2. Can you pass me that $\boxed{\text{silla}}$ so I can join the conversation?
   3. After the event, please stack the $\boxed{\text{sillas}}$ neatly against the wall.
   4. I found a comfortable $\boxed{\text{silla}}$ in the corner and settled down to relax.

Notion of Meaning for words

1. Does this context help you understand the word silla?

1. The silla is by the window, offering a nice view of the garden.
2. Can you pass me that silla so I can join the conversation?
3. After the event, please stack the sillas neatly against the wall.
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Notion of Meaning for words

1. Does this context help you understand the word silla?
2. { positioned near a window or against a wall or in the corner, used for conversing/events, can be used to relax }

1. The silla is by the window, offering a nice view of the garden.
2. Can you pass me that silla so I can join the conversation?
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Notion of Meaning for words

1. How did we do that?

Notion of Meaning for words

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2. "We searched for other words that can be used in the same contexts, found some, and made a conclusion that silla has to mean similar to those words."

Notion of Meaning for words

1. Distributional Hypothesis: Words that frequently appear in similar contexts have a similar meaning

Distributed Representations

1. Representation/meaning of a word should consider its context in the corpus

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2. Use many contexts of a word to build up a representation for it

Distributed Representations

1. **Co-occurrence matrix** is a way to can capture this!
    - size: $(\#\text{words} \times \#\text{words})$
    - rows: words (m), cols: context (n)
    - words and context can be of same or different size

Distributed Representations

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

Co-occurrence matrix

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

Co-occurrence matrix

1. Very sparse

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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

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2. $\begin{bmatrix} & & \\ & X & \\ & & \end{bmatrix}_{m\times n} =$

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

SVD on the Co-occurrence matrix

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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

SVD on the Co-occurrence matrix

1. Before the SVD, representations were the rows of X

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2. How do we reduce the representation size with SVD ?

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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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1. $W_{\text{word}} \in \mathbb{R}^{m \times k}$ $(k \ll |V| = m)$ are considered the representation of the words

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1. $W_{\text{word}} \in \mathbb{R}^{m \times k}$ $(k \ll |V| = m)$ are considered the representation of the words
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

A bit more clever things...

1. Entries in the occurrence matrix can be weighted (HAL model)

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3. ....

Count-based vs prediction-based models

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

Count-based vs prediction-based models

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

Word2Vec

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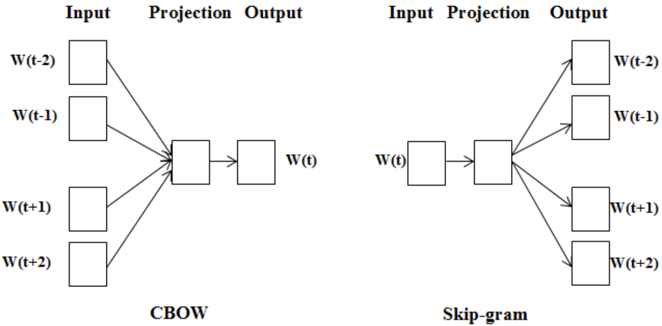
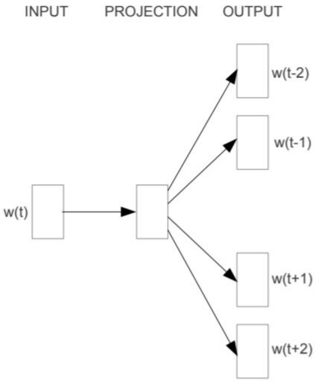
2. Two versions: Predict words from the contexts (or contexts from words)
3. Continuous Bag of Words (CBoW) and Skip-gram

Word2Vec

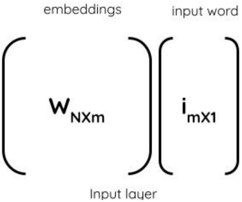

Input
Projection
Output
W(t-2)
W(t-1)
W(t+1)
W(t+2)
W(t)
CBOW
Input
Projection
Output
W(t)
W(t-2)
W(t-1)
W(t+1)
W(t+2)
Skip-gram

Word Embeddings: Skip-gram



Skip-gram

Word Embeddings: Skip-gram



Word Embeddings: Skip-gram

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Word Embeddings: Skip-gram

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2. Process the text with a sliding window (one word at a time)

1. At each step, there is a central word and context words (other words in the window)
2. Given the central word, compute the probabilities for the context words
3. Modify the word embeddings to increase these probabilities

Word Embeddings: Skip-gram

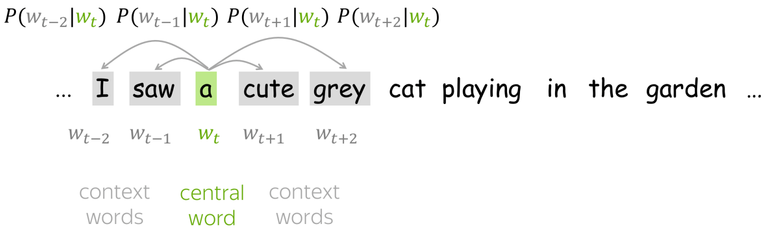
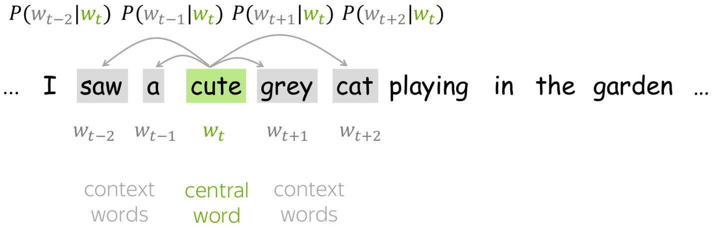


Figure from Lena Voita

Word Embeddings: Skip-gram



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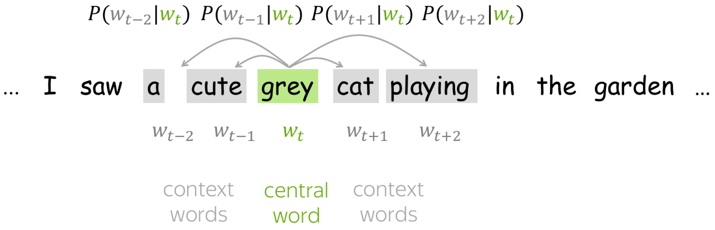

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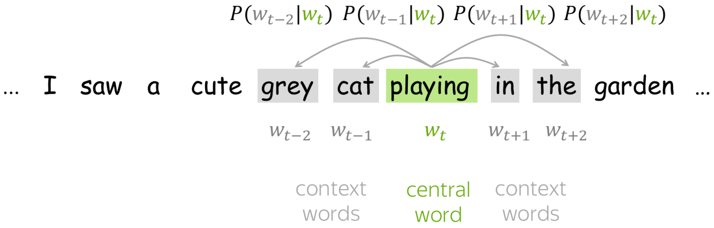

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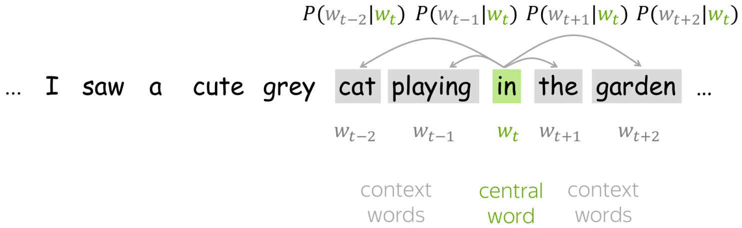


Figure from Lena Voita

Word Embeddings: Skip-gram

- For each position in $t = 1, 2, \ldots T$ in the corpus, Skip-gram predicts the context words in $m-$sized window (θ is the variables to be optimized)

$$\text{Likelihood} \quad L(\theta) = \prod_{t=1}^{T} \prod_{-m \leq j \leq m, j \neq 0} P(w_{t+j} | w_t, \theta)$$

Word Embeddings: Skip-gram

- The loss is mean NLL

$$\text{Loss} \quad J(\theta) = -\frac{1}{T}\prod_{t=1}^{T}\prod_{-m\leq j\leq m, j\neq 0} \log P(w_{t+j}|w_t, \theta)$$

Word Embeddings: Skip-gram

- What are the parameters (θ) to be learned?

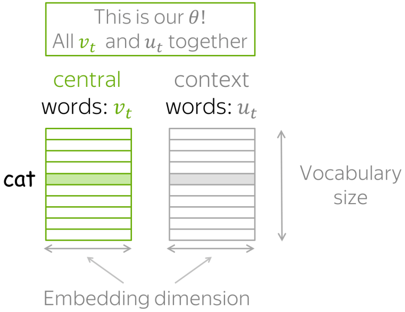


Figure from Lena Voita

Word Embeddings: Skip-gram

- How to compute $P(w_{t+j}|w_t, \theta)$?

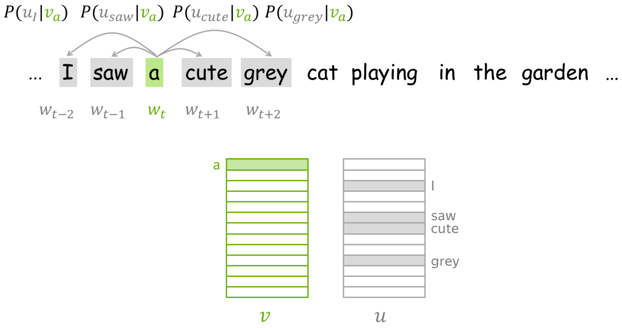
$$P(o|c) = \frac{\exp(\boxed{u_o^T v_c})}{\sum_{w \in V} \exp(u_w^T v_c)}$$

Dot product: measures similarity of o and c
Larger dot product = larger probability

Normalize over entire vocabulary
to get probability distribution

Figure from Lena Voita

Word Embeddings: Skip-gram



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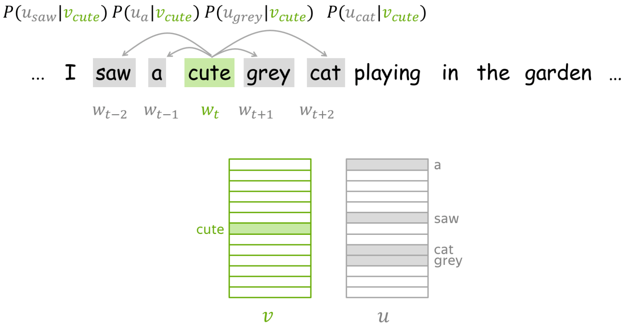

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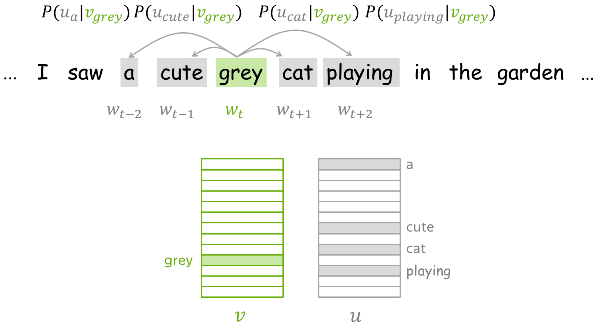

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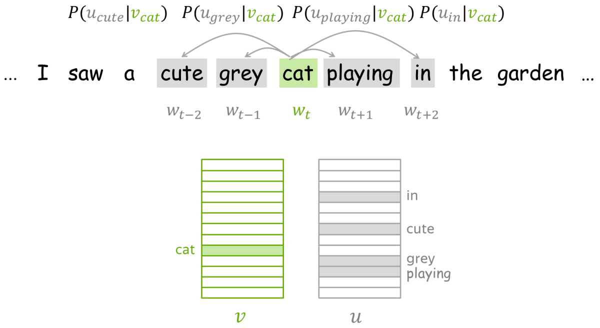

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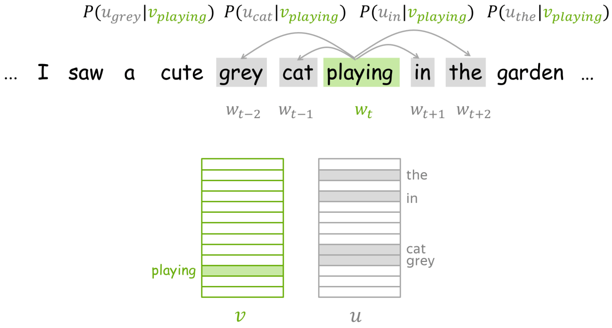

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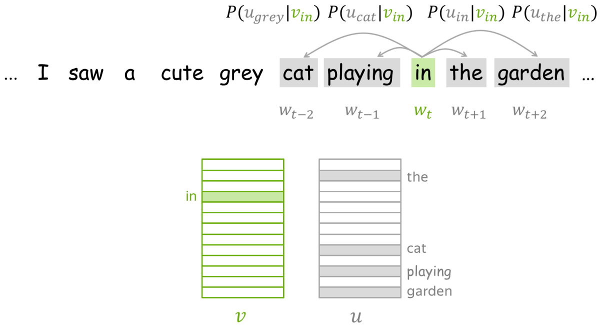

Figure from Lena Voita

Word Embeddings: Skip-gram

- Train using Gradient Descent

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- For one word at a time, i.e., (a center word, one of the context words)

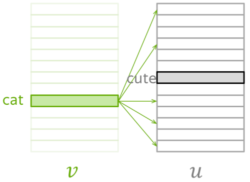
Word Embeddings: Skip-gram

- Train using Gradient Descent
- For one word at a time, i.e., (a center word, one of the context words)
- $J_{t,j}(\theta) = -\log P(cute|cat) = -\log \frac{\exp u_{cute}^T v_{cat}}{\sum_{w \in Voc} \exp u_w^T v_{cat}} =$

  $-u_{cute}^T v_{cat} + \log \sum_{w \in Voc} \exp u_w^T v_{cat}$

Word Embeddings: Skip-gram

1. Take dot product of v_{cat} with **all** u 2. exp 3. sum all



$u_{w1}^T v_{cat} \rightarrow \exp(u_{w1}^T v_{cat})$

$u_{w3}^T v_{cat} \rightarrow \exp(u_{w3}^T v_{cat})$

$\vdots$

$\boxed{u_{cute}^T v_{cat}} \rightarrow \exp(u_{cute}^T v_{cat})$

$\vdots$ 1

$u_{wn}^T v_{cat} \rightarrow \exp(u_{wn}^T v_{cat})$

$$\boxed{\sum_{w \in V} \exp(u_w^T v_{cat})}$$

2

4. get loss (for this one step)

$$J_{t,j}(\theta) = \underbrace{-u_{cute}^T v_{cat}}_{1} + \underbrace{\log \sum_{w \in V} \exp(u_w^T v_{cat})}_{2}$$

5. evaluate the gradient, make an update

$$v_{cat} := v_{cat} - \alpha \frac{\partial J_{t,j}(\theta)}{\partial v_{cat}}$$

$$u_w := u_w - \alpha \frac{\partial J_{t,j}(\theta)}{\partial u_w} \ \forall\, w \in V$$

Figure from Lena Voita

Word Embeddings: Skip-gram

- Training is slow (for each central word, all the context words need to be updated)

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- Negative sampling: not all the context words are considered, but a random sample of them

Word Embeddings: Skip-gram

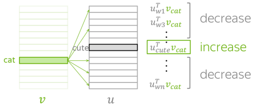
- Training is slow (for each central word, all the context words need to be updated)
- Negative sampling: not all the context words are considered, but a random sample of them
- Training over a large corpus leads to sufficient updates for each vector

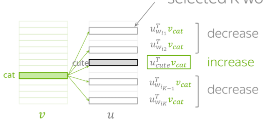
Word Embeddings: Skip-gram

Dot product of v_{cat}:
- with u_{cute} - increase,
- with all other u - decrease

Dot product of v_{cat}:
- with u_{cute} - increase,
- with a subset of other u - decrease

Negative samples: randomly selected K words





Parameters to be updated:
- v_{cat}
- u_w for all w in the vocabulary

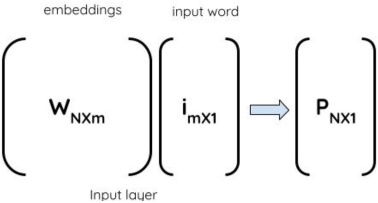
|V| + 1 vectors

Parameters to be updated:
- v_{cat}
- u_{cute} and u_w for w in K negative examples

K + 2 vectors

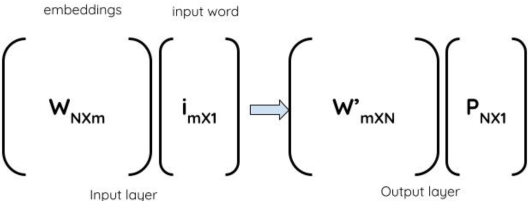
Figure from Lena Voita

Word Embeddings: Skip-gram



Can be viewed as a Neural Network

Word Embeddings: Skip-gram



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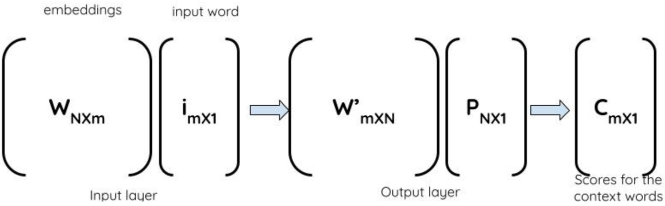

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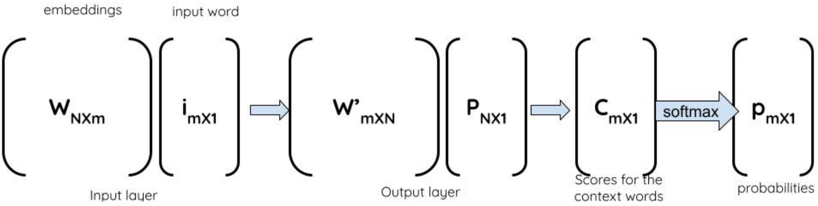

Can be viewed as a Neural Network

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1. $W_{N \times m}$ is the W_{word} (used for representing the words)

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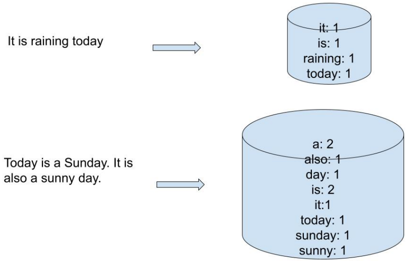
2. $W'_{m \times N}$ is the W_{context} (may be ignored after the training)

Word Embeddings: Skip-gram

1. $W_{N\times m}$ is the W_{word} (used for representing the words)
2. $W'_{m\times N}$ is the W_{context} (may be ignored after the training)
3. Some showed averaging word and context vectors may be more beneficial

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

CBoW

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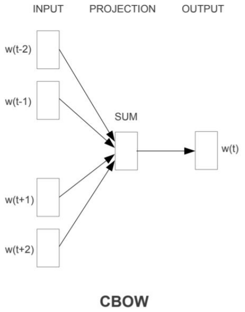
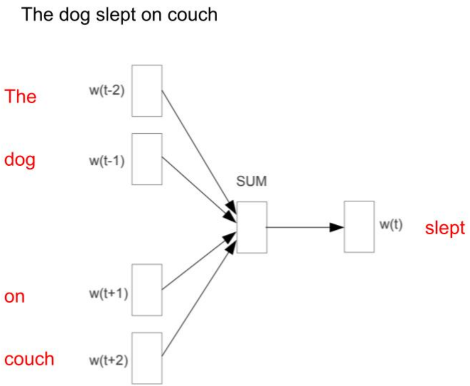
2. Adds them (order is lost) for predicting the target word



CBoW



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

CBoW

1. Size of the vocabulary $= m$

CBoW

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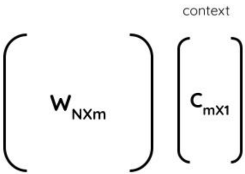
2. Dimension of the embeddings $= N$

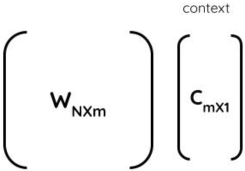
Word Embeddings: CBoW

1. Input layer $W_{N\times m}$ (embeddings for the context words) projects the context (sum of 1-hot vectors of all the context vectors) into N-dim space



Word Embeddings: CBoW

1. Input layer $W_{N \times m}$ (embeddings for the context words) projects the context (sum of 1-hot vectors of all the context vectors) into N-dim space
2. Representations of all the $(2h)$ words in the context are summed (result is an N-dim context vector)



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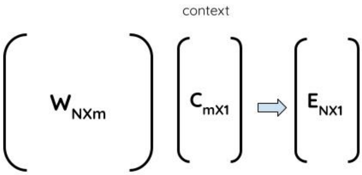

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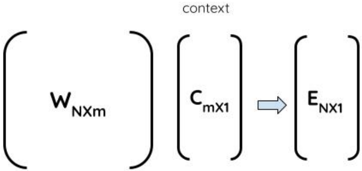

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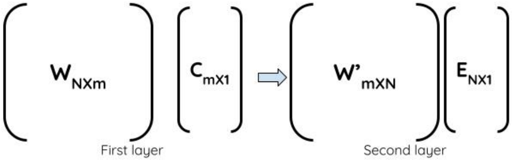

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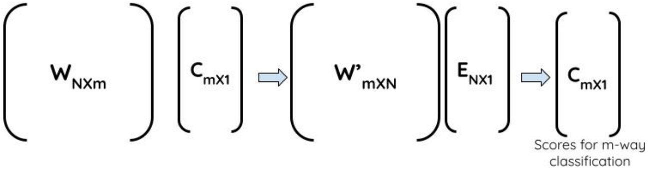
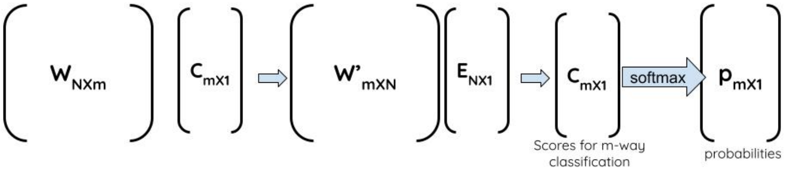


Word Embeddings: CBoW

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



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Glove

1. Glove - Global Vectors

Glove

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2. Combines the score-based and predict-based approaches

Glove

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Glove

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Glove

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   - v_i - central representation of word i, c_j - context representation of word j
3. Similarly, $v_j^T c_i = \log P(i/j) = \log X_{ij} - \log X_j$ (aim is to learn such embeddings v_i and c_i)

Glove

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2. $v_i^T c_j + b_i + \tilde{b_j} = \log X_{ij}$
3. Since $\log X_i$ and $\log X_j$ depend on the words i and j, they can be considered as the word specific biases (learnable)

Glove

1. Learning objective becomes
$$\underset{v_i, c_j, b_i, \tilde{b_j}}{\operatorname{argmin}} \ J() = \sum_{i,j} \left(v_i^T c_j + b_i + \tilde{b_j} - \log X_{ij}\right)^2$$

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2. Much of the entries in the co-occurrence matrix are zeros (noisy or less informative)
3. Suggests to apply a weight

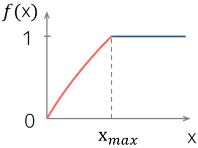
Glove

context vector | word vector | bias terms (also learned)

$$J(\theta) = \sum_{w,c\,\in V} \underbrace{f(\mathrm{N}(w,c))}_{} \cdot \left(u_c^T v_w + b_c + \overline{b_w} - \log \mathrm{N}(w,c)\right)^2$$

Weighting function to:

- penalize rare events
- not to over-weight frequent events



$$f(x) = \begin{cases} (x/x_{max})^{\alpha} & \text{if } x < x_{max}, \\ 1 & \text{otherwise.} \end{cases}$$

$\alpha = 0.75$, $x_{max} = 100$

Figure from Lena Voita

Evaluating the embeddings

1. Intrinsic - studying the internal properties (how well they capture the meaning: word similarity, analogy, etc.)

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2. Extrinsic - studying how they perform a task

Analysing the embeddings

1. Walking the semantic space

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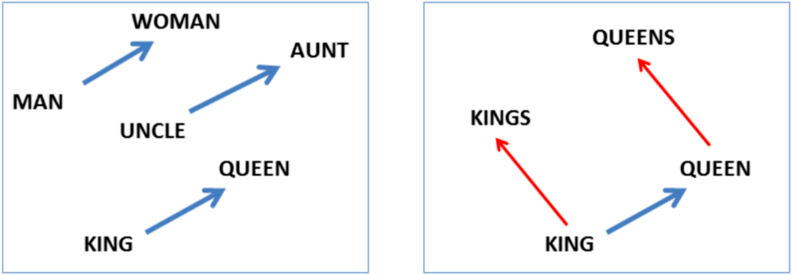
1. Walking the semantic space
2. Structure - (form clusters) nearest neighbors have a similar meaning, Linear structure

Glove

semantic: $v(\textbf{king}) - v(\textbf{man}) + v(\textbf{woman}) \approx v(\textbf{queen})$

syntactic: $v(\textbf{kings}) - v(\textbf{king}) + v(\textbf{queen}) \approx v(\textbf{queens})$



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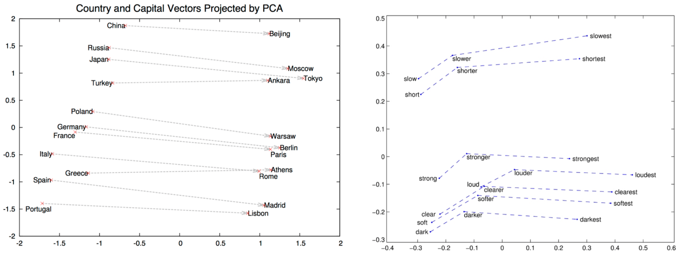
Glove



Word2Vec GloVe

Figure from Lena Voita