Deep Learning for Computer Vision

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Word Embeddings

1. Text processing with NNs require to encoding into vectors

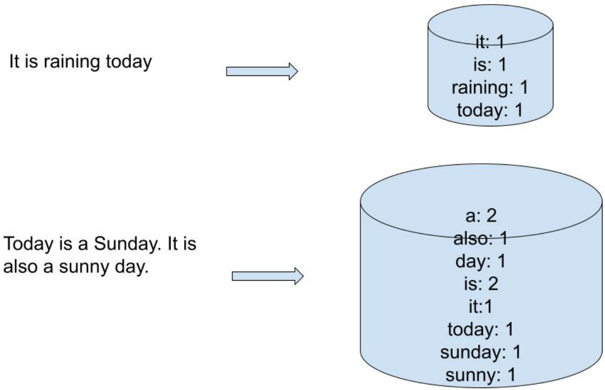
One-hot encoding

1. One-hot encoding: N words encoded as binary vectors of length N

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

Bag of Words (BoW)

1. Bag of Words: Collection and frequency of words



Drawbacks

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3. Doesn't capture language structure

Word Embeddings: idea

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2. Expecting that similar words fall nearby in the space

Word Embeddings

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2. Trade-off: greater capacity vs. efficiency

Word Embeddings

1. Finding W: as a part of a prediction task that involves neighboring words

Word Embeddings: word2vec

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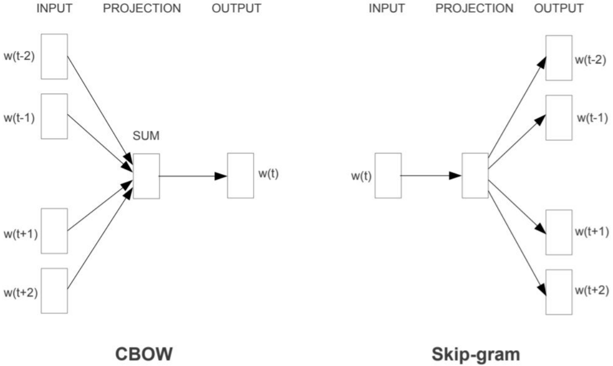
3. Two versions: Continuous Bag of Words (CBoW) and Skip-gram



Word Embeddings: CBoW

1. Considers the embeddings of 'n' words before and 'n' words after the target word

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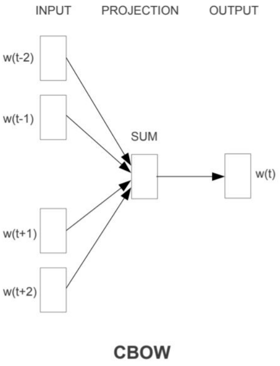
2. Adds them (order is lost) for predicting the target word



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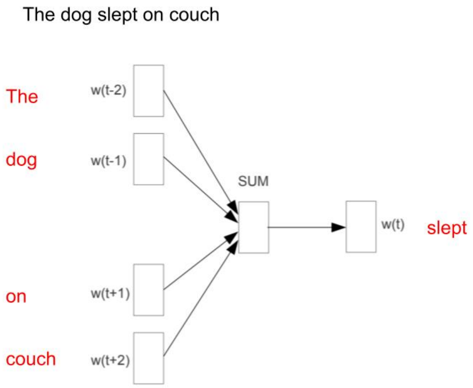

Word Embeddings: CBoW

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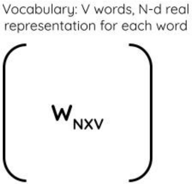

Word Embeddings: CBoW

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

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

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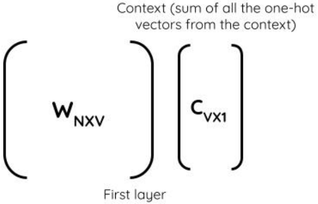

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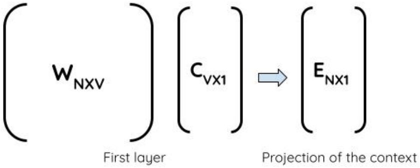

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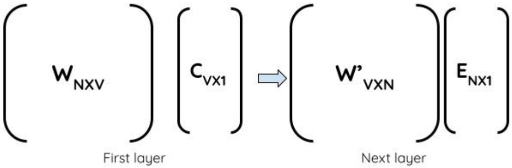

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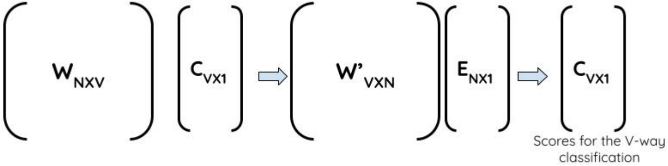
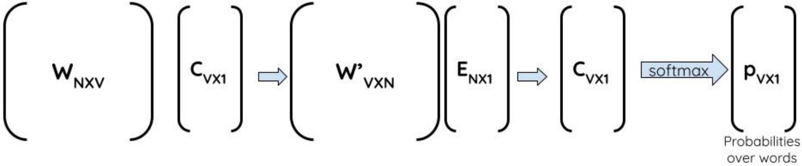


Word Embeddings: CBoW

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



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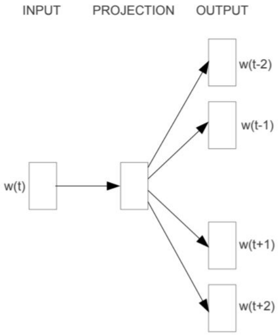
2. Or, take the average of both the representations

Word Embeddings: Skipgram

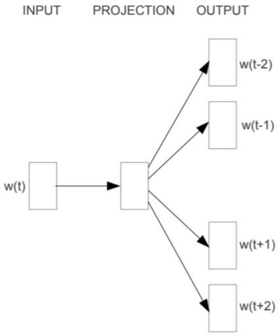
1. Predicts surrounding words given current word



Skip-gram

Word Embeddings: Skipgram

1. Predicts surrounding words given current word
2. Pick a word in the context randomly, and predict that the words that form the context



Skip-gram

Word Embeddings: Skipgram

input word

$$\begin{bmatrix} \\ i_{vX1} \\ \\ \end{bmatrix}$$

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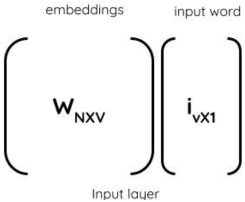

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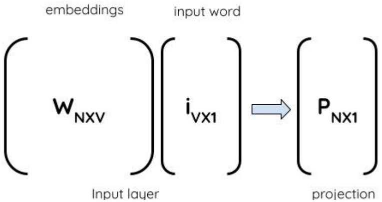

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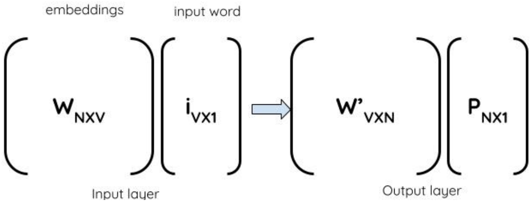

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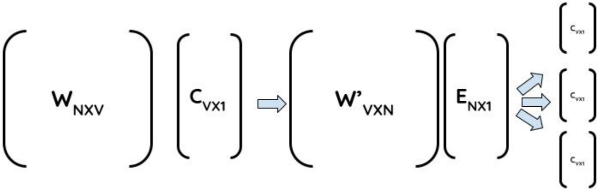

Word Embeddings: interesting results

1. W(Paris) - W(France) + W(Italy) = W(Rome)

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2. W(Man) - W(Woman) + W(King) = W(Queen)

Word Embeddings: Applications

1. Key for the success of many NLP tasks such as PoS tagging, parsing, semantic role labeling, etc.

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2. Can serve projecting multi-modal data (e.g. multiple languages, images and text, etc.)

References

1. Mikolov, Tomas; et al. (2013). "Efficient Estimation of Word Representations in Vector Space". arXiv:1301.3781