Deep Learning

8.2 Word Embeddings (CBOW)

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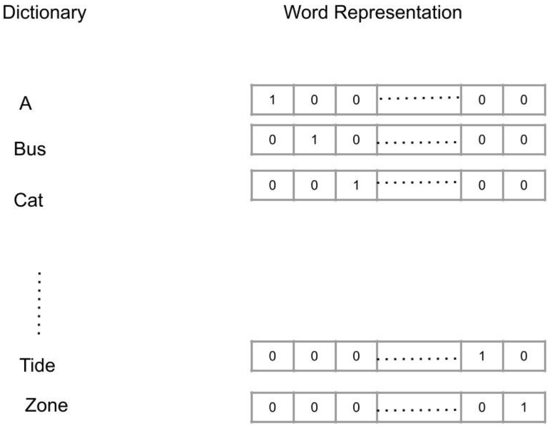
Word Embeddings

1. Text processing with NNs require to encoding into vectors

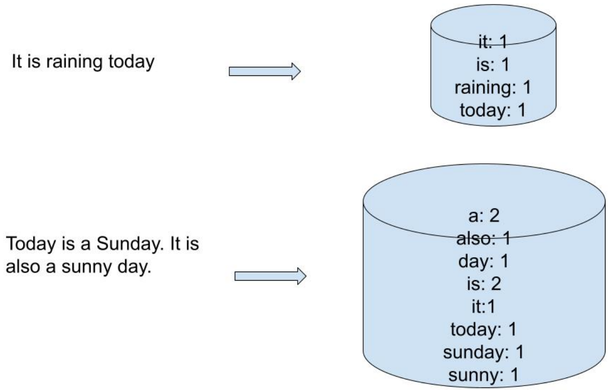
One-hot encoding

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



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

1. What is the dimension of the embedding?

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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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2. Predict words from the context

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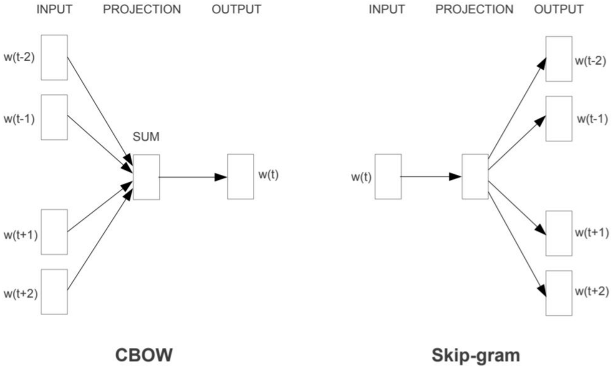
3. Two versions: Continuous Bag of Words (CBoW) and Skip-gram



Word Embeddings: CBoW

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

Word Embeddings: CBoW

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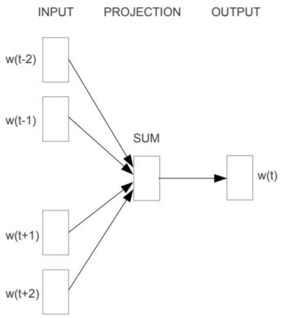
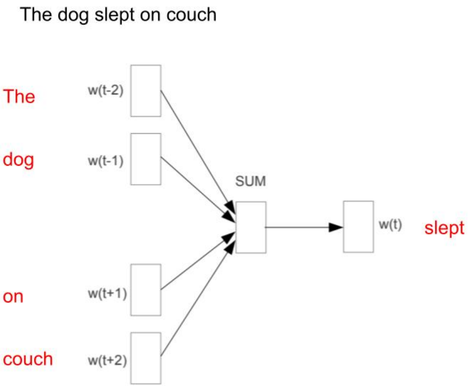
2. Adds them (order is lost) for predicting the target word



CBOW

Word Embeddings: CBoW



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Word Embeddings: CBoW

1. Size of the vocabulary $= V$
2. Dimension of the embeddings $= N$
3. Input layer will have the weight matrix $W_{N \times V}$
4. Projects the words in to N dimensional space
5. Projections of all the $(2n)$ words in context are summed (result is an Nd vector)

Word Embeddings: CBoW

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

Word Embeddings: CBoW

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2. Projects the accumulated embeddings onto the vocabulary

Word Embeddings: CBoW

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3. That is, V- way classification $\rightarrow$ (after a softmax) maximizes the probability for the target word

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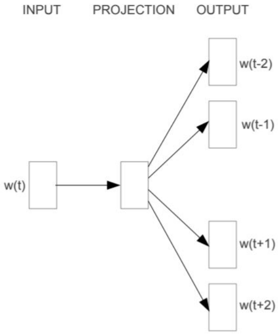
1. $W_{N \times V}$ or $W'_{V \times N}$ can be considered as the word embeddings
2. Or, take the average of both the representations

Word Embeddings: Skipgram

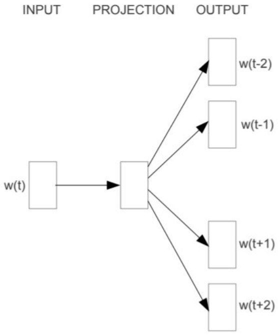
1. Predicts surrounding words given current word



Skip-gram

Word Embeddings: Skipgram

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



Skip-gram

Word Embeddings: interesting results

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

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