Distributed Representation

Discrete representation

- One-hot vector/ Bag-of-word vector

$$'dog' = \begin{bmatrix} 1\\0\\0\\0\\0 \end{bmatrix}$$
 $'cat' = \begin{bmatrix} 0\\1\\0\\0 \end{bmatrix}$ $Doc1 = \begin{bmatrix} 12\\0\\0\\3\\1\\0\\5 \end{bmatrix}$

Distributed representation

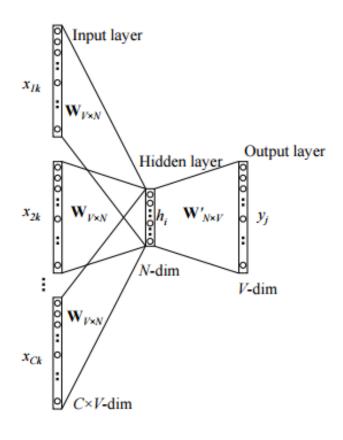
- Word2vec, Doc2vec

$$'dog' = \begin{bmatrix} 1\\0\\0\\0\\0 \end{bmatrix} \quad 'cat' = \begin{bmatrix} 0\\1\\0\\0\\0 \end{bmatrix} \quad Doc1 = \begin{bmatrix} 12\\0\\0\\3\\1\\0\\5 \end{bmatrix} \quad 'dog' = \begin{bmatrix} 0.5\\0.3\\-0.1\\1 \end{bmatrix} \quad 'cat' = \begin{bmatrix} 0.8\\-0.3\\-0.2\\0.6 \end{bmatrix} \quad Doc1 = \begin{bmatrix} 0.68\\0.23\\0.10\\-0.41\\0.90\\0.51\\-0.33 \end{bmatrix}$$

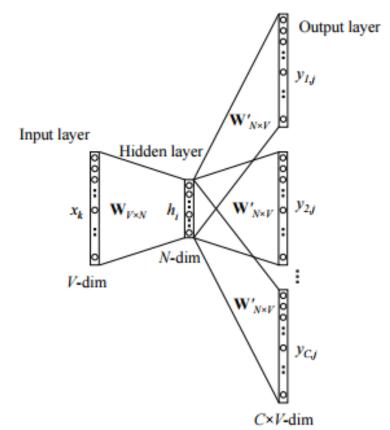
- Frequency 기반으로 표현하는 방법
- 구성 변수들을 직관적으로 이해 가능함
- 전처리 과정이 뚜렷하지 않으며 단어 빈도가 낮은 경우 중요하지 않게 판별됨

- Neural Network를 통해 continuous vector로 변환 가능
- 단어 별 유사도 계산가능
 - 'king' 'man' + 'woman' → closest('Queen')

Data: All Bloomberg news articles from 2008 to 2015, # = 520,728



Continuous bag-of-word model



Skip-gram model

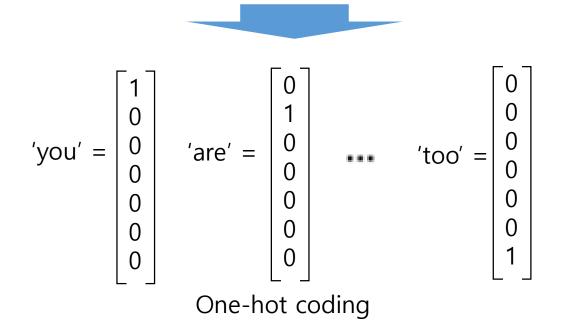
V = vocabulary size

- C = window size

 $N = word2vec\ dimension$

Doc1: { 'You are a very good boy.'
'You are a good girl too.' }

Vocabulary: { 'you' 'are' 'a' 'very' 'good' 'girl', 'too' }



Continuous bag-of-word model

N-dim

Hidden layer

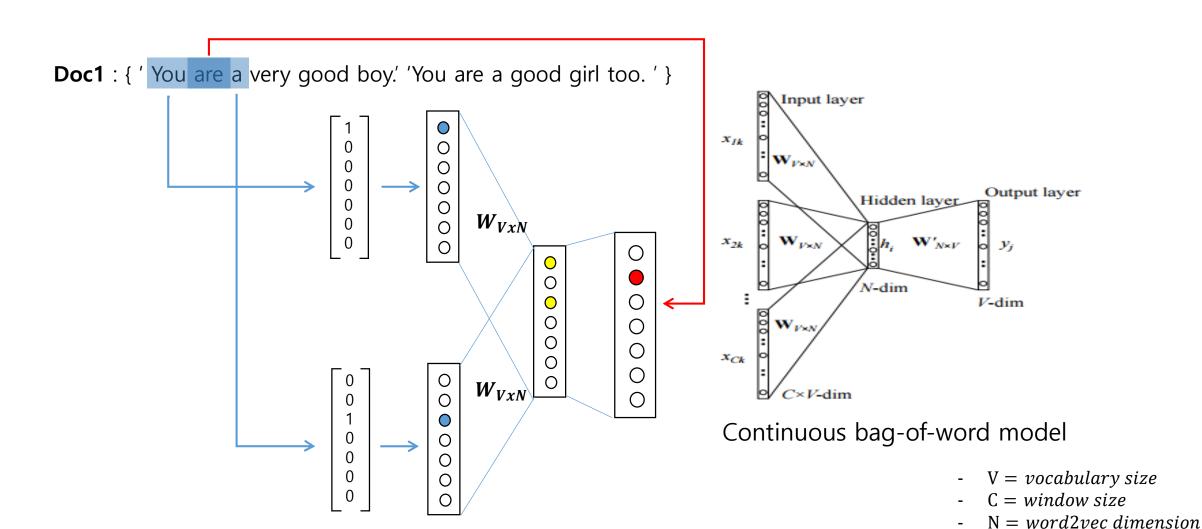
Input layer

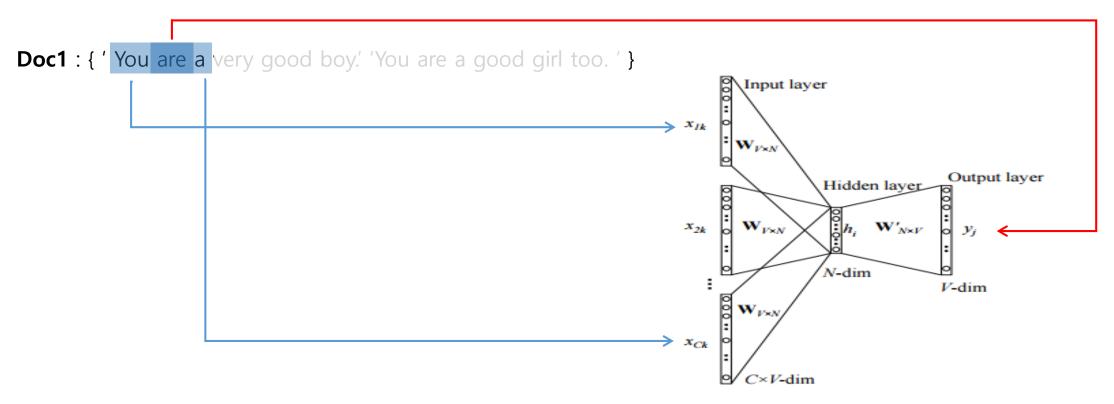
- V = vocabulary size
- C = window size

Output layer

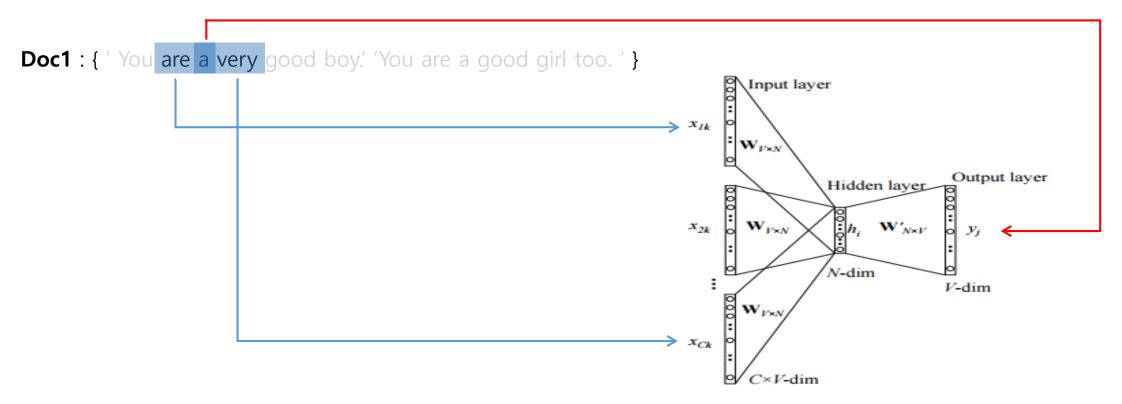
V-dim

- N = word2vec dimension

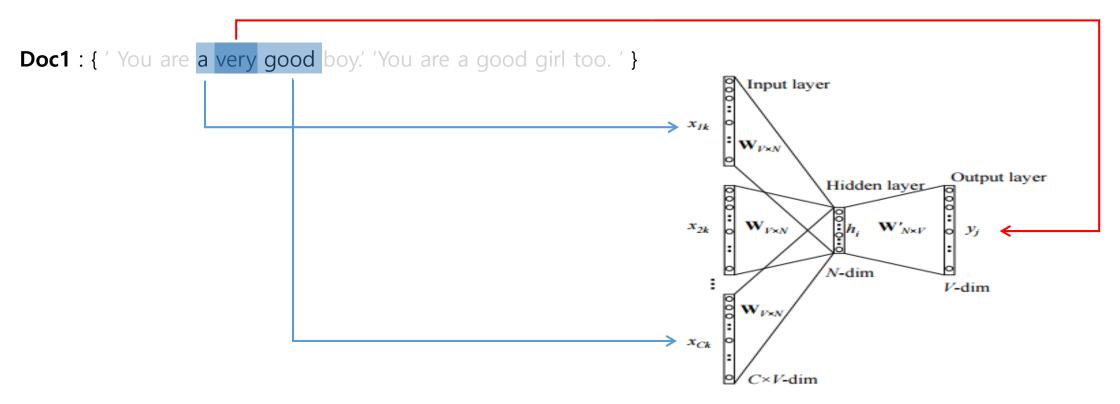




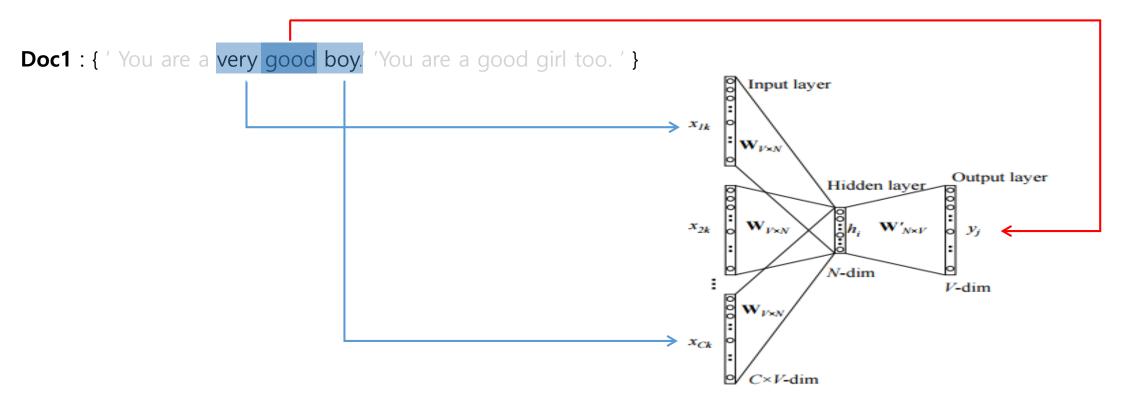
- V = vocabulary size
- C = window size
- N = word2vec dimension



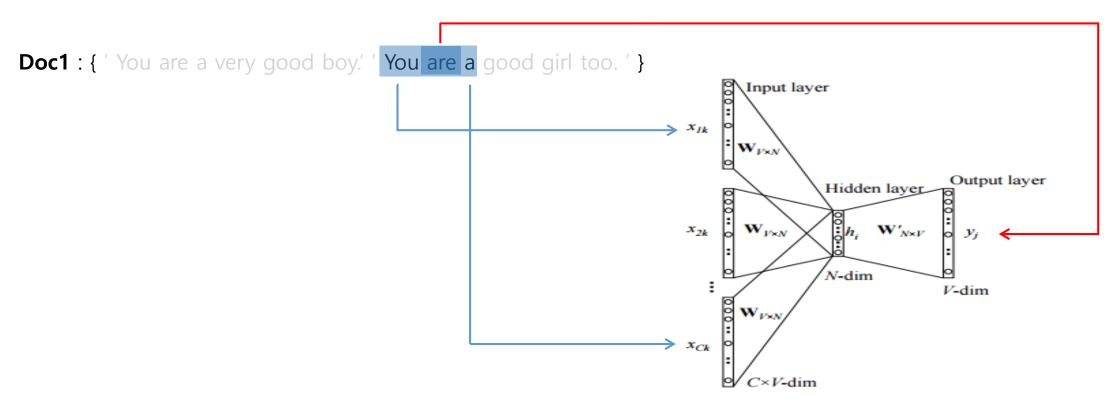
- V = vocabulary size
- C = window size
- $N = word2vec\ dimension$



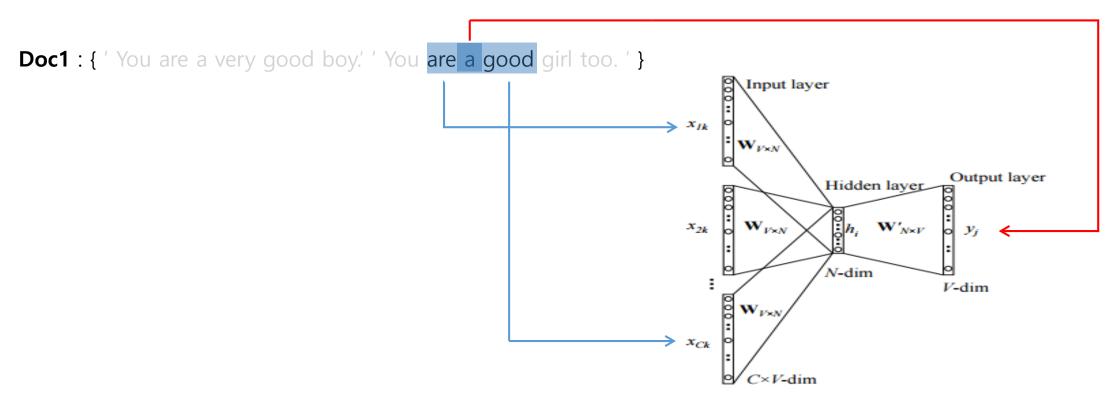
- V = vocabulary size
- C = window size
- $N = word2vec\ dimension$



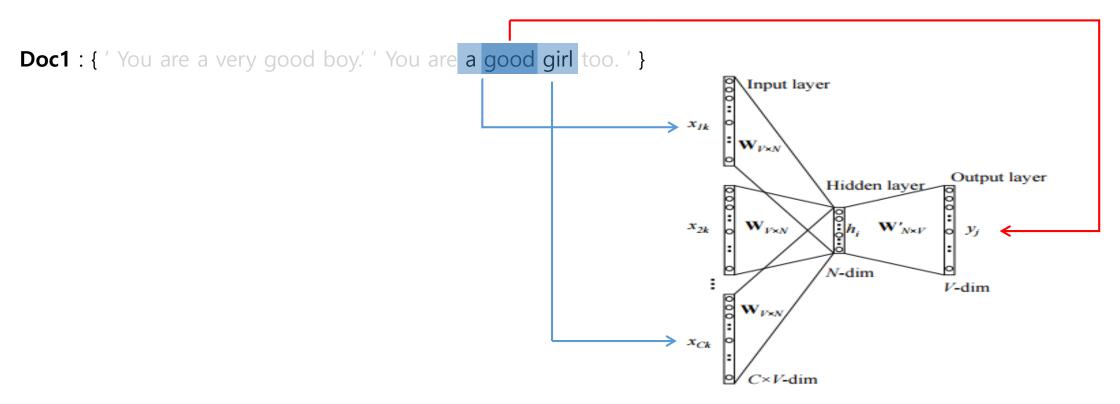
- V = vocabulary size
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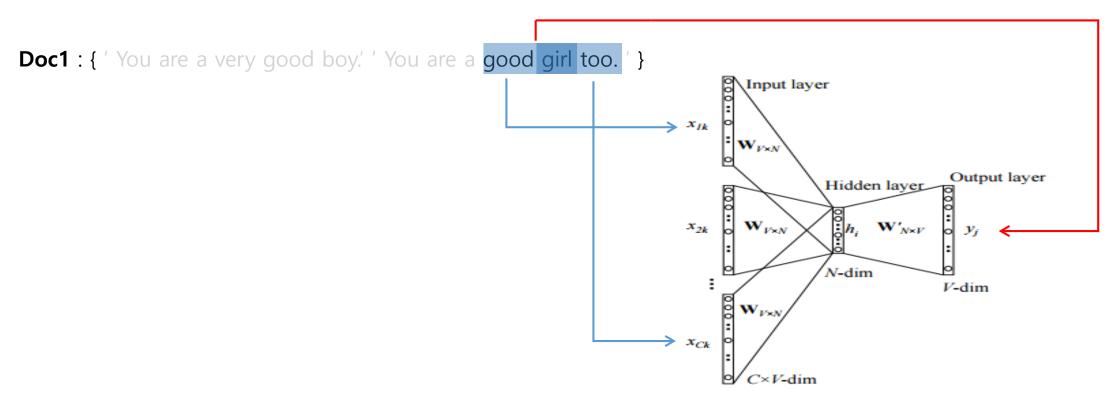
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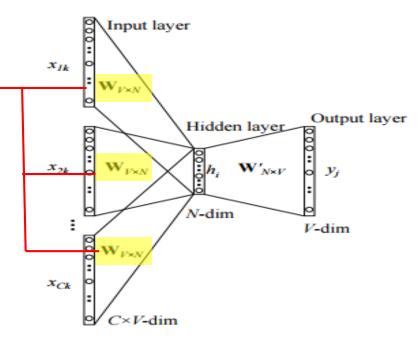


- V = vocabulary size
- C = window size
- $N = word2vec\ dimension$

Doc1: { 'You are a very good boy.' 'You are a good girl too. ' }

 $W_{VxN} \leftarrow$

	X1	X2	Х3	X4	X 5	Xn
Word 1	0.345	0.121	-0.538	1.011	2.011	0.004
Word2	0.445	2.101	1.054	-0.181	-0.114	0.764
•••	ver		***	•••	100	
word V	0.334	-0.087	-0.407	1.114	0.554	0.674

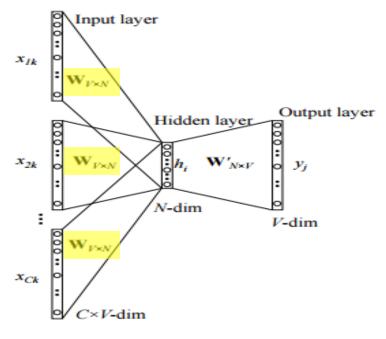


- V = vocabulary size
- C = window size
- N = word2vec dimension

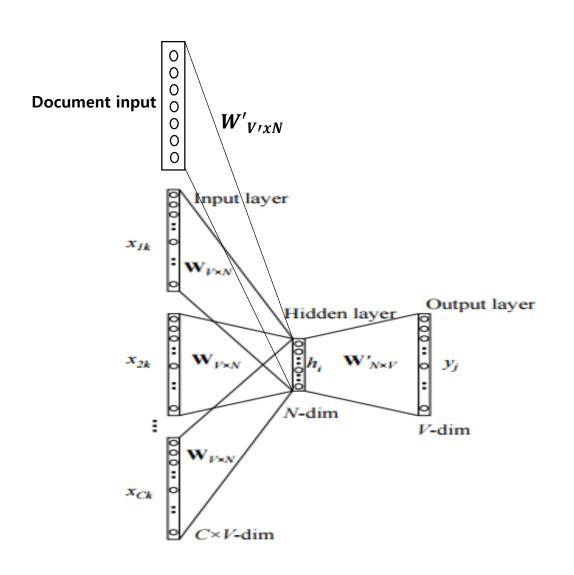
Doc1: { 'You are a very good boy.' 'You are a good girl too. ' }

W_{VxN}

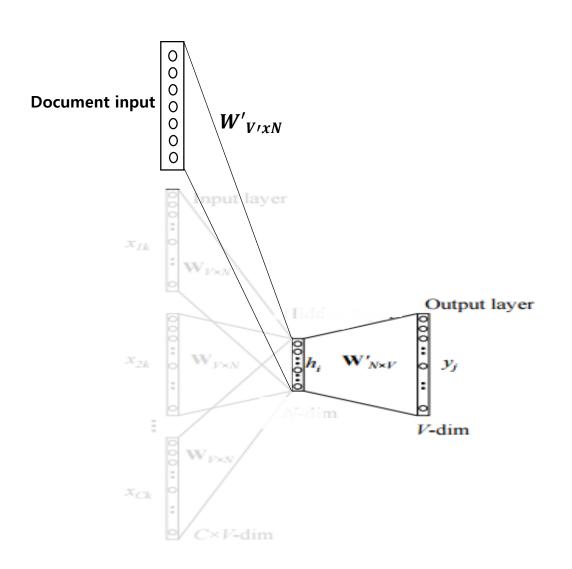
	X1	X2	Х3	X4	X5	Xn
Word 1	0.345	0.121	-0.538	1.011	2.011	0.004
Word2	0.445	2.101	1.054	-0.181	-0.114	0.764
•••					•••	•••
word V	0.334	-0.087	-0.407	1.114	0.554	0.674



- V = vocabulary size
- C = window size
- N = word2vec dimension



- V = vocabulary size
- V' = documents size
- C = window size
- N = $doc2vec\ dimension$



- V = vocabulary size
- V' = documents size
- C = window size
- N = $doc2vec\ dimension$

