Word Representation

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Example:
High, Low , Hotel, Resort

$$w^{High} = \begin{bmatrix} 1 \\ 0 \\ 0 \\ 0 \end{bmatrix}, w^{Low} = \begin{bmatrix} 0 \\ 1 \\ 0 \\ 0 \end{bmatrix}, W^{Hotel} = \begin{bmatrix} 0 \\ 0 \\ 1 \\ 0 \end{bmatrix}, w^{Resort} = \begin{bmatrix} 0 \\ 0 \\ 0 \\ 1 \end{bmatrix}$$

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Problem with One Hot Vector

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  Hotel and Resort are synonyms but vector are not similar
  Hotel = [0 0 1 0]
  Resort = [0 0 0 1]

Learn encode similarity in the vectors themselves

Word Vector - Word2Vec

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- Context of word w in text is a set of words (within a fixed-size window) that appear nearby.
- Contexts are used to construct a representation of w

Word Representation - Word2Vec - Context

. . . government debt problems turning into **banking** crises as happened in 2009. . .

. . . saying that Europe needs unified **banking** regulation to replace the hodgepodge. . .

. . . India has just given its **banking** system a shot in the arm. . .

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Word2vec (Mikolov et al. 2013) [1] is a framework for learning word vectors.

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- Keep adjusting the word vectors to maximize this probability.

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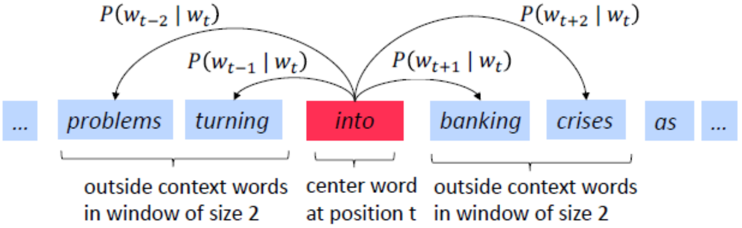
Word Representation - Word2Vec

Example windows and process for computing $P(w_{t+1}|w_t)$



http://web.stanford.edu/class/cs224n/slides/cs224n-2019-lecture01-wordvecs1.pdf

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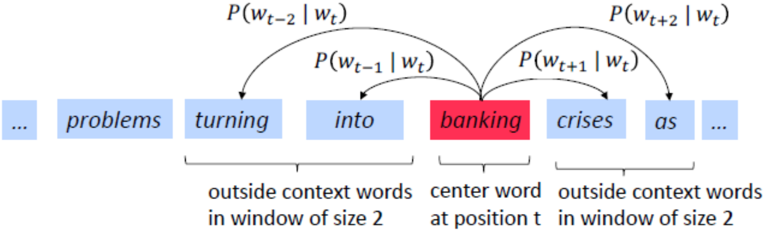

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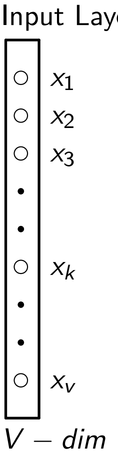
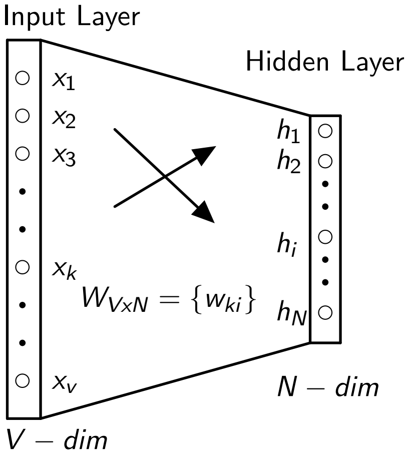
Word Representation - Word2Vec - CBOW



A simple CBOW model with only one word in the context

$V =$ Vocabulary size $N =$ Word embedding vector size

Word Representation - Word2Vec - CBOW



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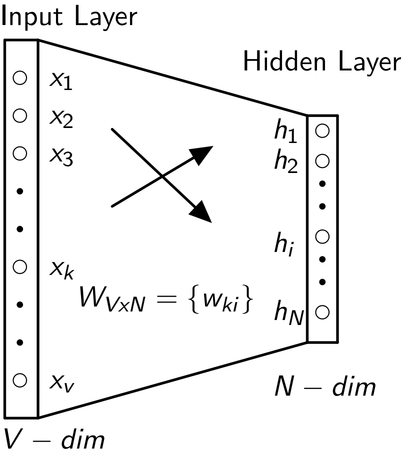

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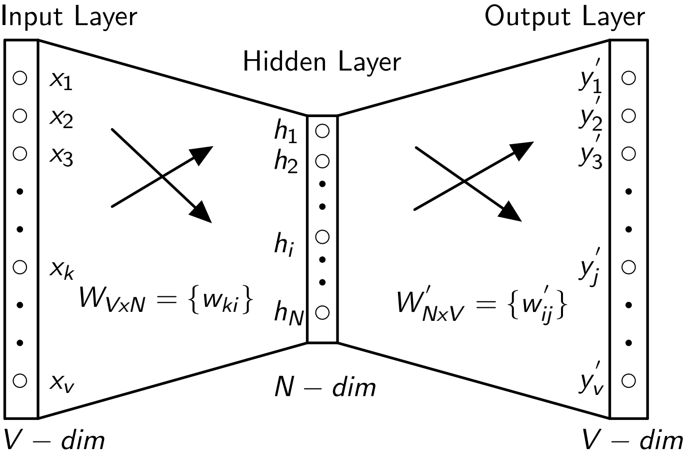

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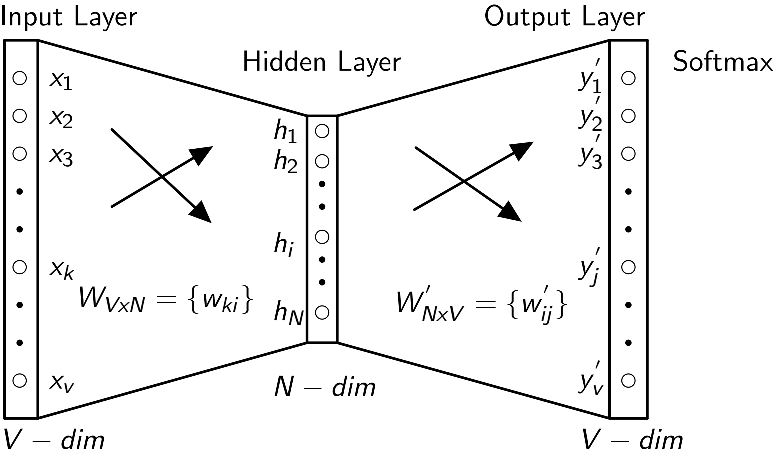

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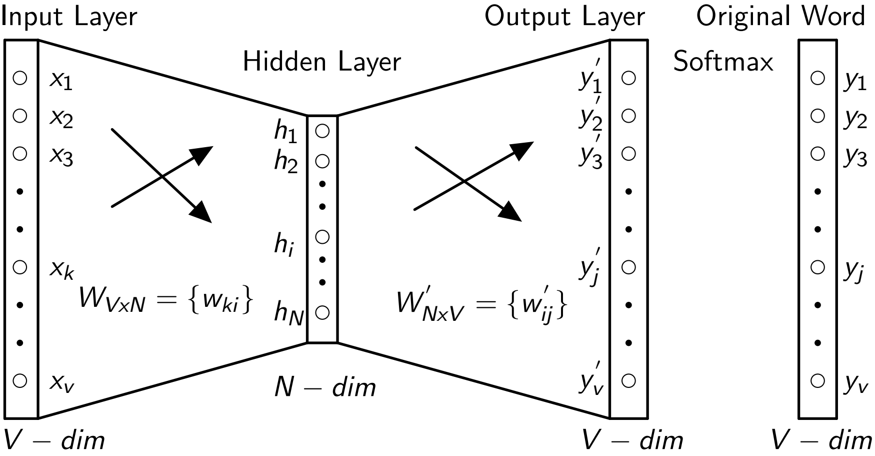

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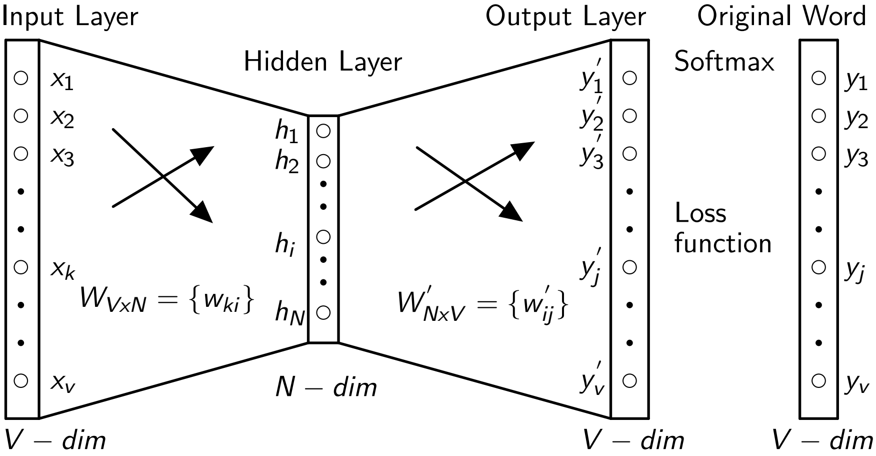

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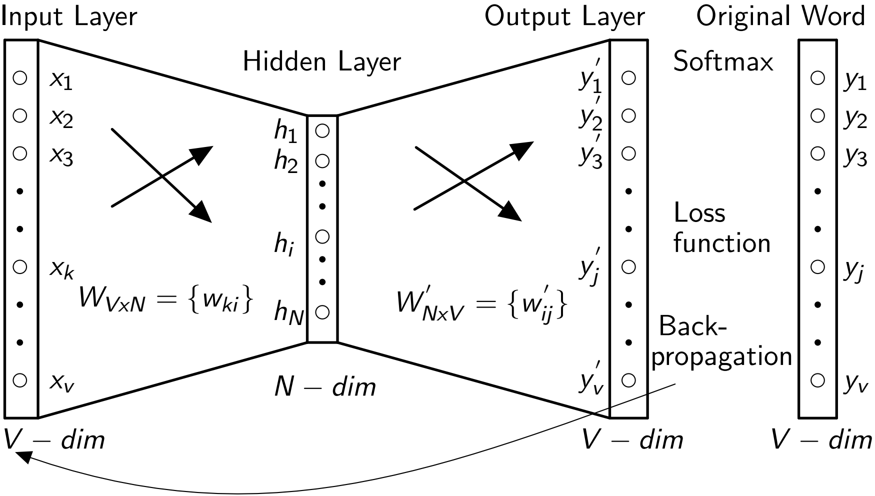

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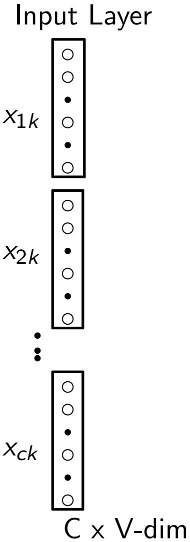
Word Vector - Word2Vec - CBOW

Example: How we take word embedding/ word vector from Weight $W'_{N \times V}$

$$[0 \quad 0 \quad 0 \quad \boxed{1} \quad 0] \times \begin{bmatrix} 17 & 24 & 1 \\ 23 & 5 & 7 \\ 4 & 6 & 13 \\ \boxed{10} & \boxed{12} & \boxed{19} \\ 11 & 18 & 25 \end{bmatrix} = [10 \quad 12 \quad 19]$$

https://israelg99.github.io/2017-03-23-Word2Vec-Explained/

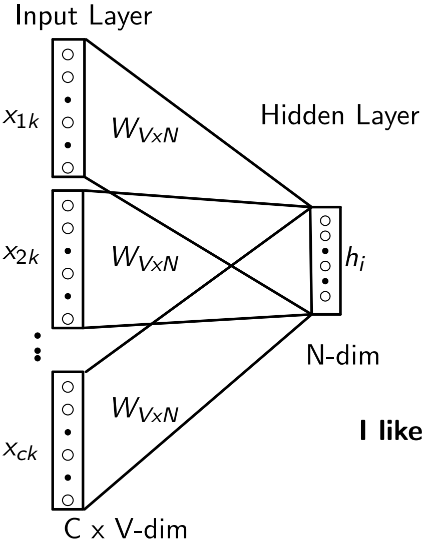
Word Vector - Word2Vec - CBOW



I like **playing** **football with** friend

CBOW Architecture

Word Vector - Word2Vec - CBOW



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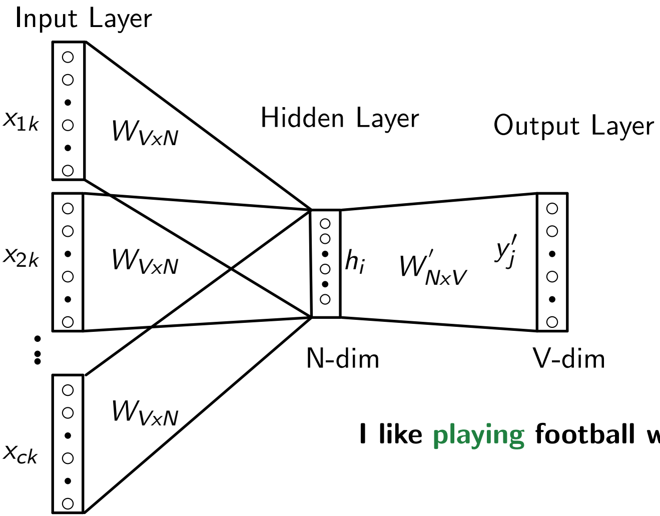

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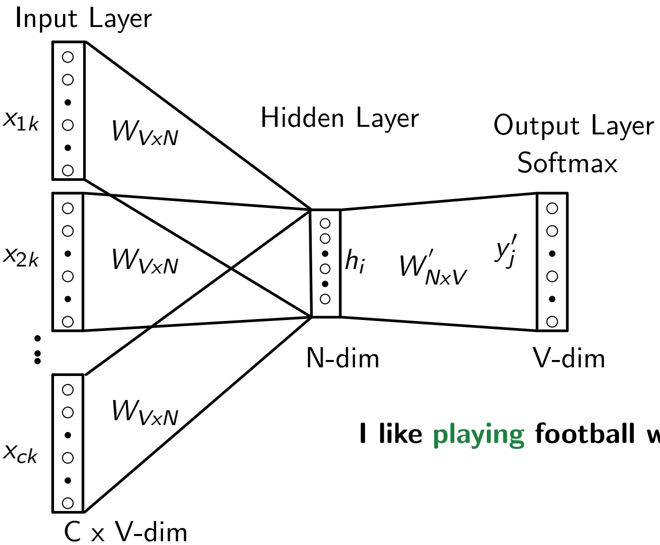

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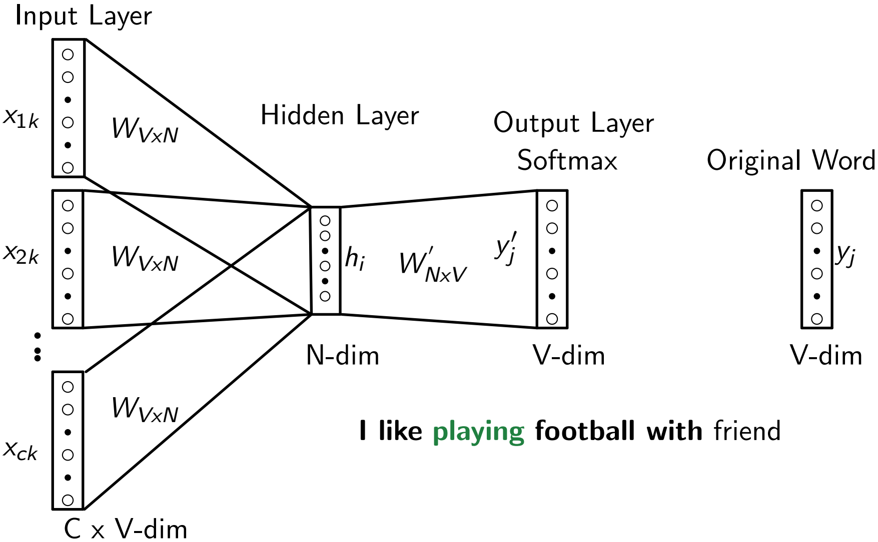

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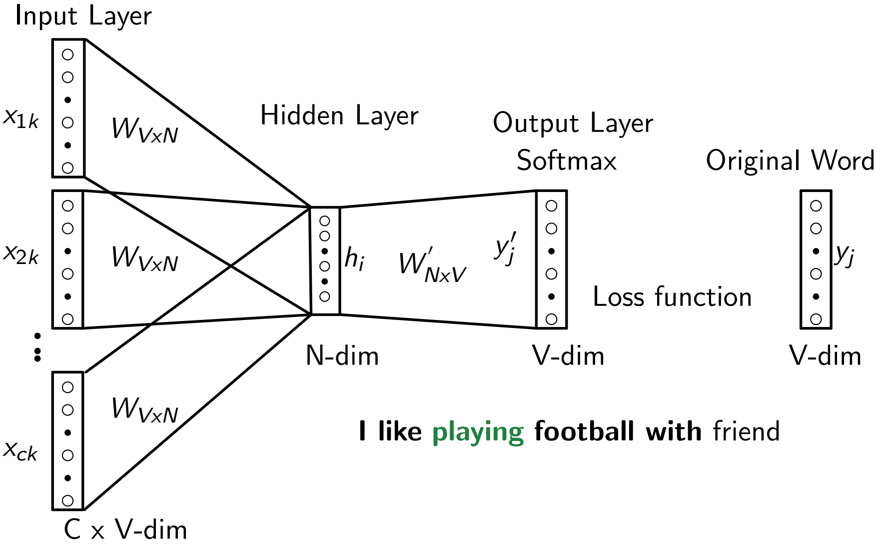

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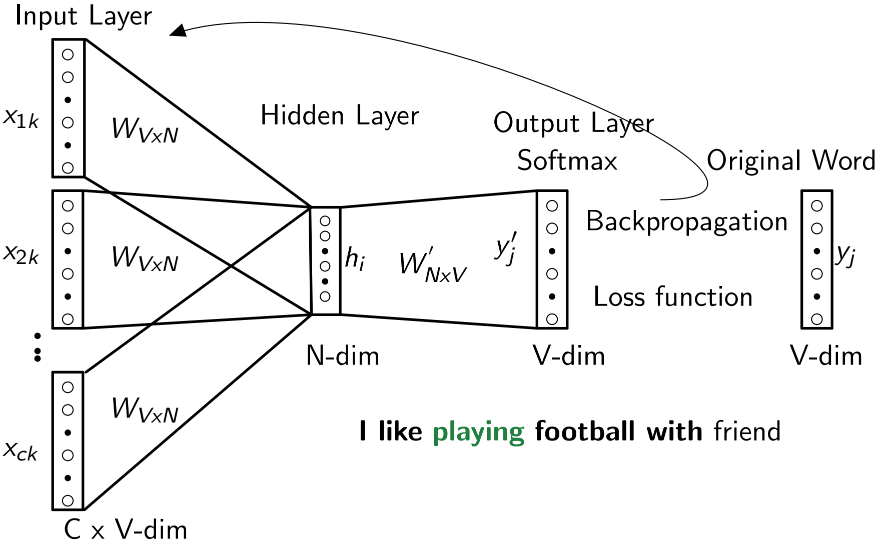

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CBOW Architecture

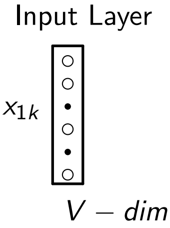
Word Representation - Word2Vec - CBOW

- Input layer takes the one hot encoded vectors of the context words as input.
- Two sets of weights
  1. between input layer and hidden layer (size - VxN)
  2. between input layer and hidden layer (size - NxV)
- Input is multiplied with input-hidden weights and hidden input is multiplied with hidden-output weights to produce a output vector.
- Output vector is then passed through a softmax function which gives the probability of target word w.r.t each context word.
- Target word is the one hot encoding representation of the word
- Error between output and target is calculated and then update weights.

Word Representation - Word2Vec - CBOW - Softmax

- Simply calculates probability of occurrence of the target word w.r.t. the context word
- Consider that target word is denoted by vector u_c and context words are denoted by vectors $\hat{v}$.
- The probability sums to 1

$$P(u_c|\hat{v}) = \frac{exp(u_c^T \hat{v})}{\sum_{j=1}^{|V|} exp(u_j^T \hat{v})}$$



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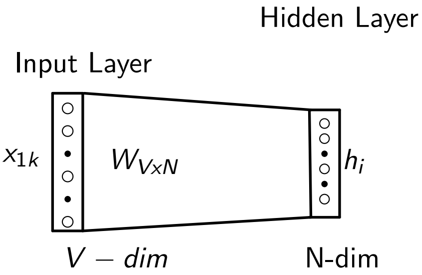
Skip-gram Architecture

Word Representation - Word2Vec - Skip gram



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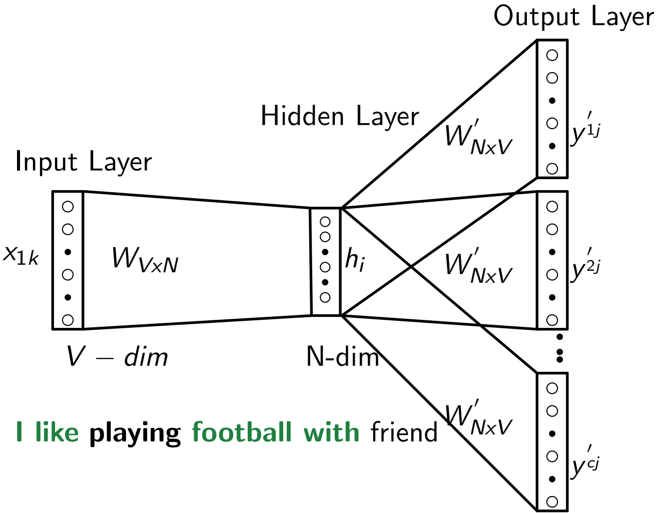

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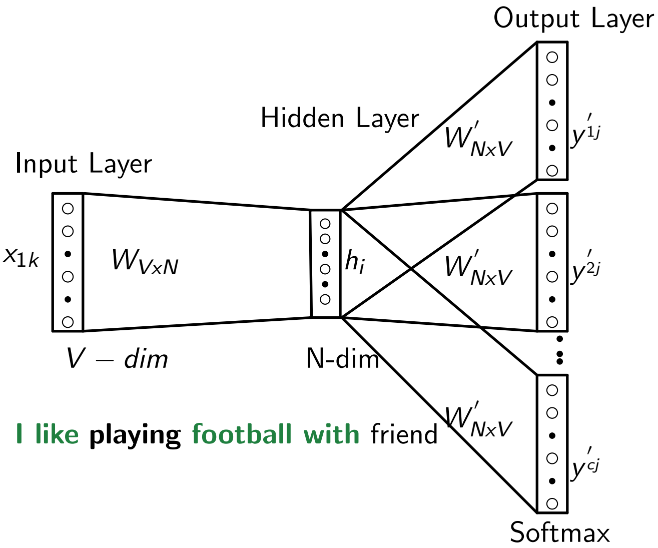

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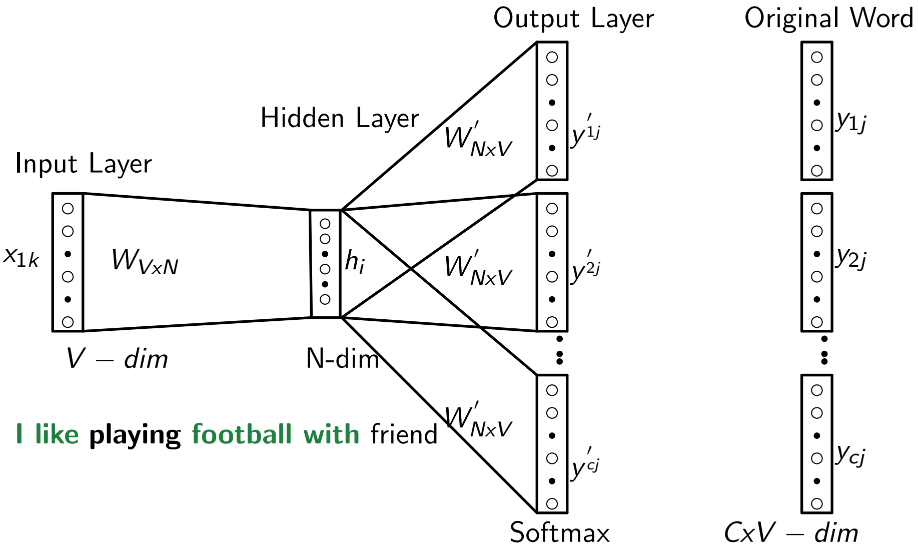

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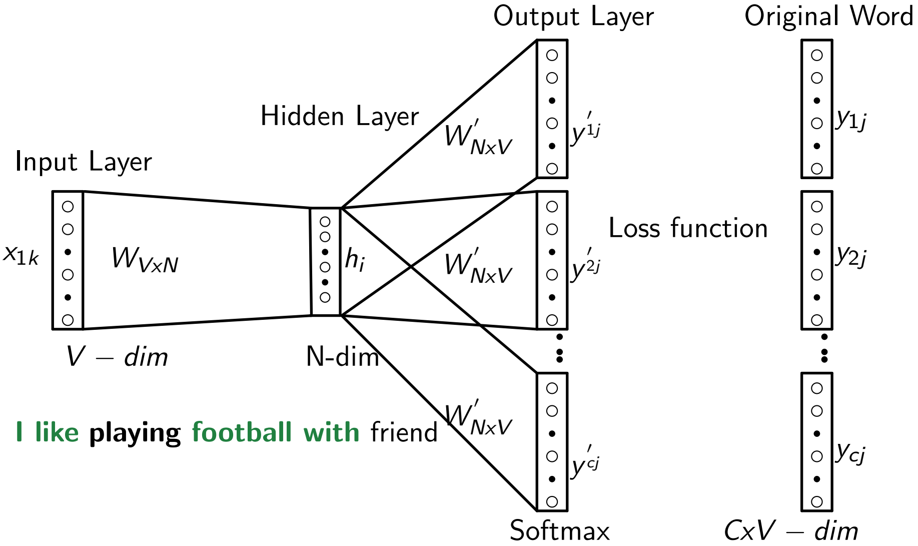

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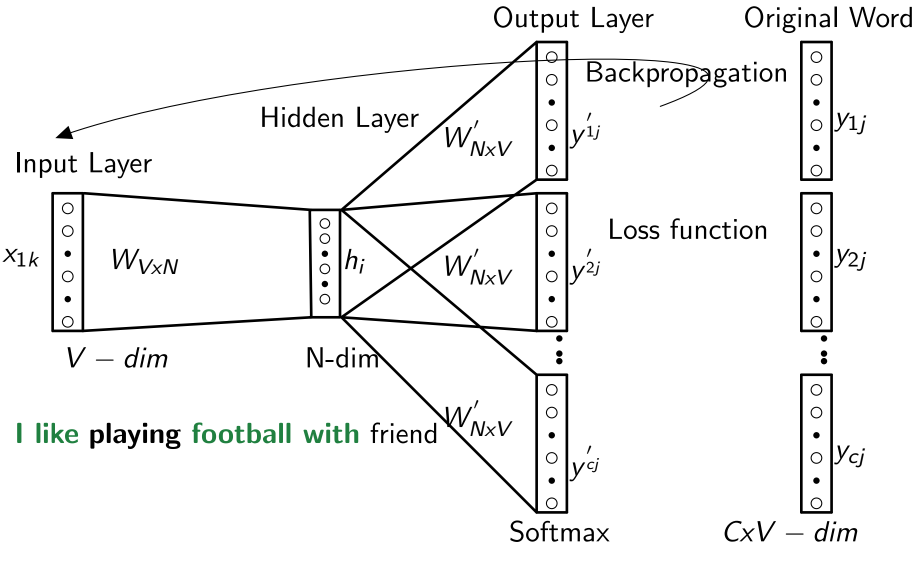

Skip-gram Architecture

Word Representation - Word2Vec - Skip gram

- One hot encoded vector of target word is taken as input and multiplied with VxN input hidden matrix.
- Hidden layer is multiplied with hidden output matrix to give the output vectors.
- Take softmax function over the output vectors and then calculate the error between the actual vector and the predicted vectors and backpropagate to update the weights.

Word Representation - Word2Vec - Objective Function

- For each position $t = 1, \ldots, T$, predict context words within a window of fixed size m, given center word w_j.

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

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- Require to look local information and global information of a corpus.