Lecture 7

WORD REPRESENTATION LEARNING

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Contents

- Word Representation
  - Word Vectorization
  - Word Embedding
- Word2Vec
- Other models
  - GLoVE
  - FastText
  - ELMo
- Building a representation word model
- Application: Plagiarism Detection

Review - Text Document Vectorization Approaches

The meaning of a word

- Meaning:
  - the idea that is represented by a word, phrase, etc.
  - the idea that a person wants to express using words, phrases, etc.
  - the idea that is expressed in a work of writing, art, etc.
- Some commonest linguistic ways of thinking of meaning:

signifier (symbol) ⟺ signified (idea or thing)

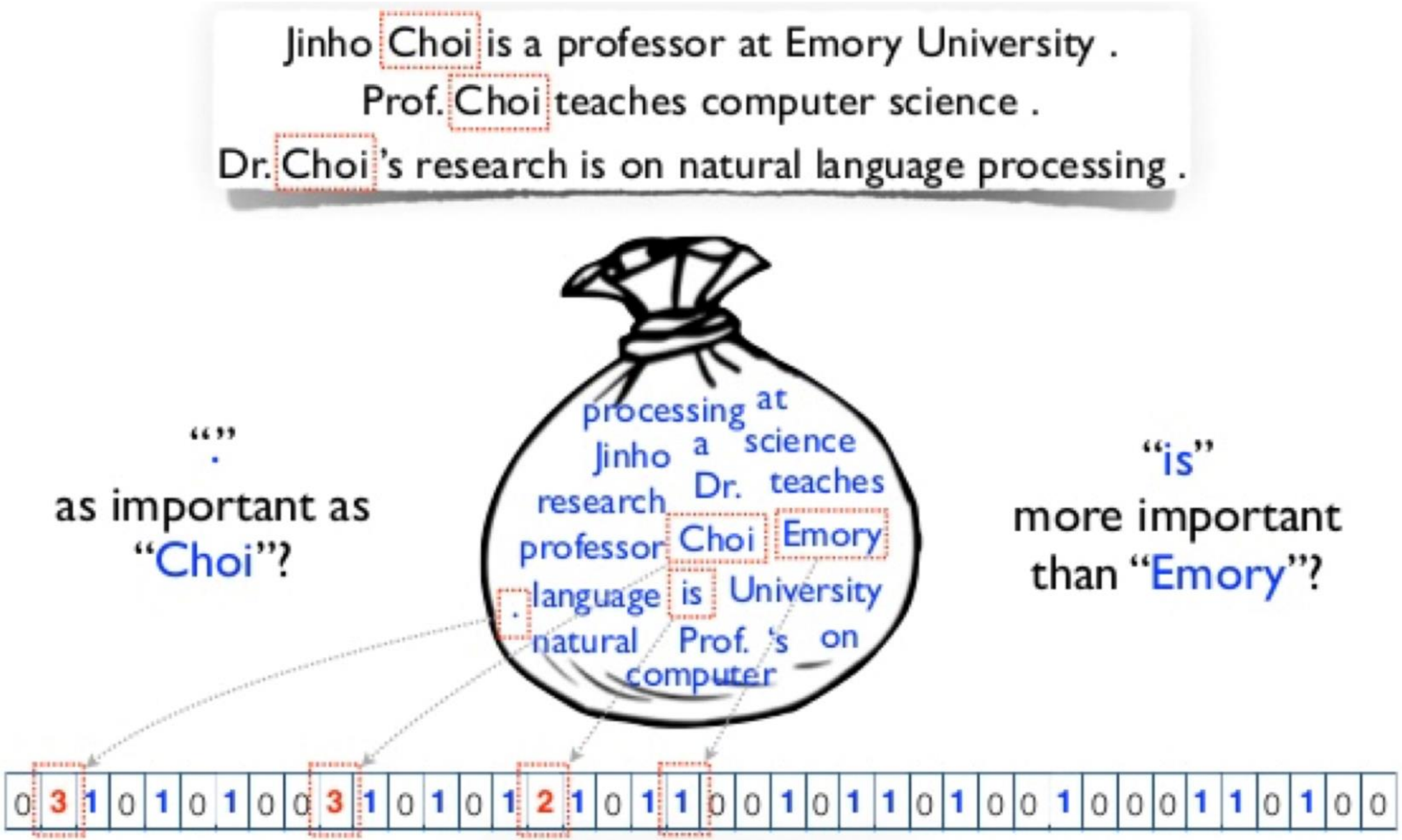
= denotational semantics

tree ⟺ {  , …}

Discrete Vector Representation

- Bag-of-words model
- Co-occurrence matrix
- TF-IDF
- One-hot encoding vector

Bag-of-words Model



Window-based co-Occurrence Matrix

- Window length = 1 (more common: 5-10)
- Symmetric (irrelevant whether left or right context)
- Example corpus:
  - I like deep learning
  - I like NLP
  - I enjoy flying

counts	I	like	enjoy	deep	learning	NLP	flying	.
I	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
.	0	0	0	0	1	1	1	0

TF-IDF

$$w_{i,j} = tf_{i,j} \times \log\left(\frac{N}{df_i}\right)$$

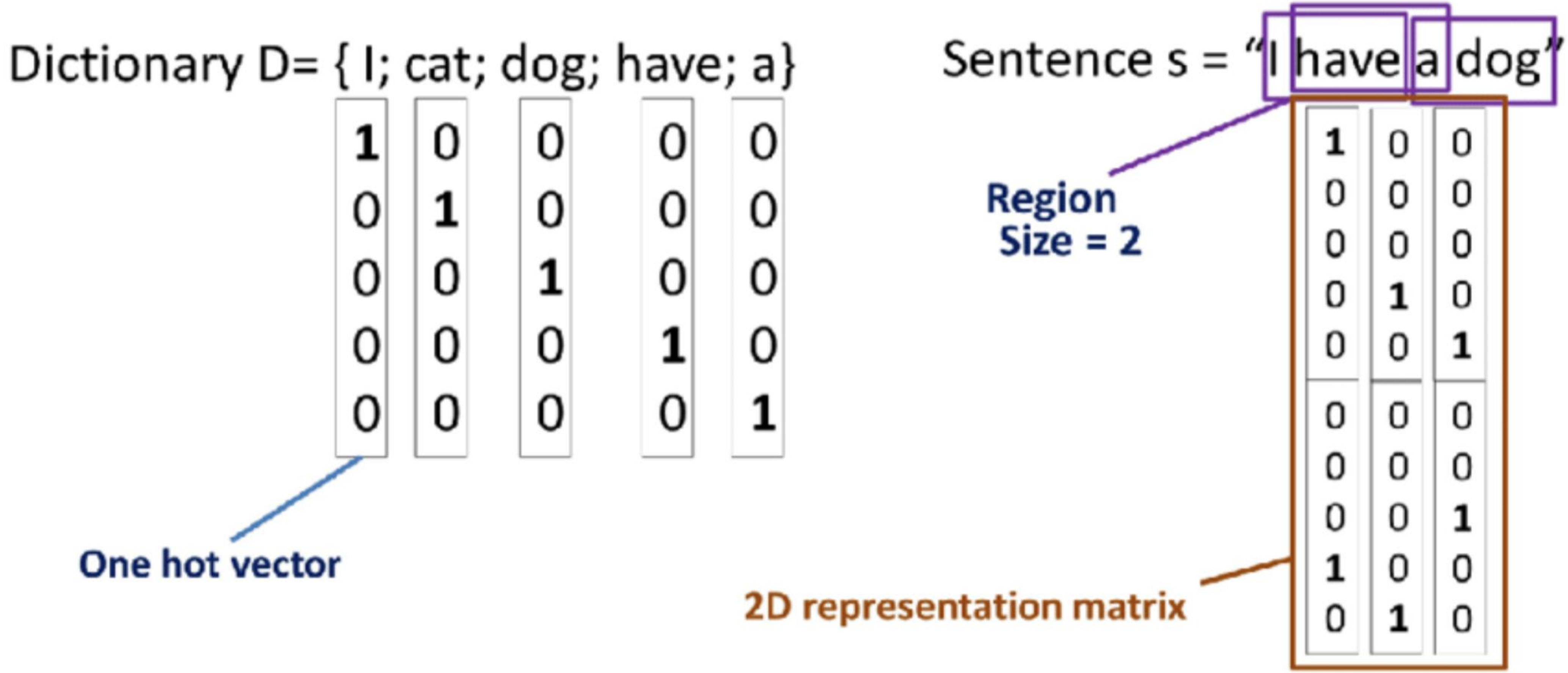
$tf_{i,j}$ = number of occurrences of i in j
df_i = number of documents containing i
N = total number of documents

	Document 1	Document 2	Document 3	Document 4	Document 5	Document 6	Document 7	Document 8
Term(s) 1	10	0	1	0	0	0	0	2
Term(s) 2	0	2	0	0	0	18	0	2
Term(s) 3	0	0	0	0	0	0	0	2
Term(s) 4	6	0	0	4	6	0	0	0
Term(s) 5	0	0	0	0	0	0	0	2
Term(s) 6	0	0	1	0	0	1	0	0
Term(s) 7	0	1	8	0	0	0	0	0
Term(s) 8	0	0	0	0	0	3	0	0

Word Vector
(Passage Vector)

Document Vector

One-hot Vector



Problems with words as discrete vectors

- Example: search for the keywords “Seattle Motel” will result also “Seattle Hotel”
- However:

  motel = [0 0 0 0 0 0 0 0 0 0 1 0 0 0 0]
  hotel = [0 0 0 0 0 0 0 1 0 0 0 0 0 0 0]

- These two vectors are orthogonal, without any notion of similarity for one-hot vectors
- Solution: **encode the similarity inside the word vector**

Word Vector Representation

Representing word by their context

- Distributional semantic: ***A word's meaning is given by the words that frequently appear close-by***
- When a word w appears in a text, its **context** is the set of words that appear nearby (within a fixed-size window)
- We will use the many contexts of w to build up a representation of w

…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…*

These context words will represent ***banking***

Word vectors

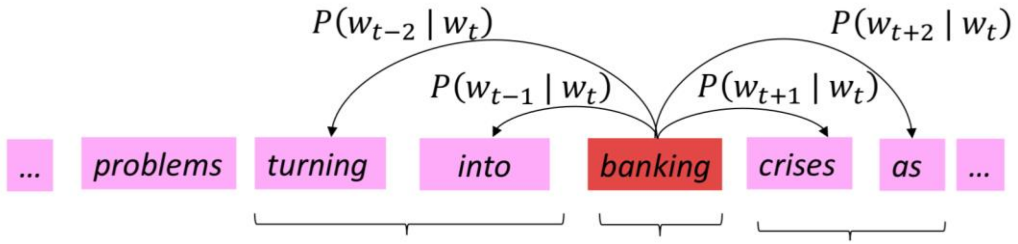
- Each word is represented by a dense vector which is chosen so that it's similar to vectors of words that appear in similar contexts
- The similarity is measured by the vector dot (scalar) product

$$banking = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix} \qquad monetary = \begin{pmatrix} 0.413 \\ 0.582 \\ -0.007 \\ 0.247 \\ 0.216 \\ -0.718 \\ 0.147 \\ 0.051 \end{pmatrix}$$

Word Embedding Model: word2vec

The main idea:

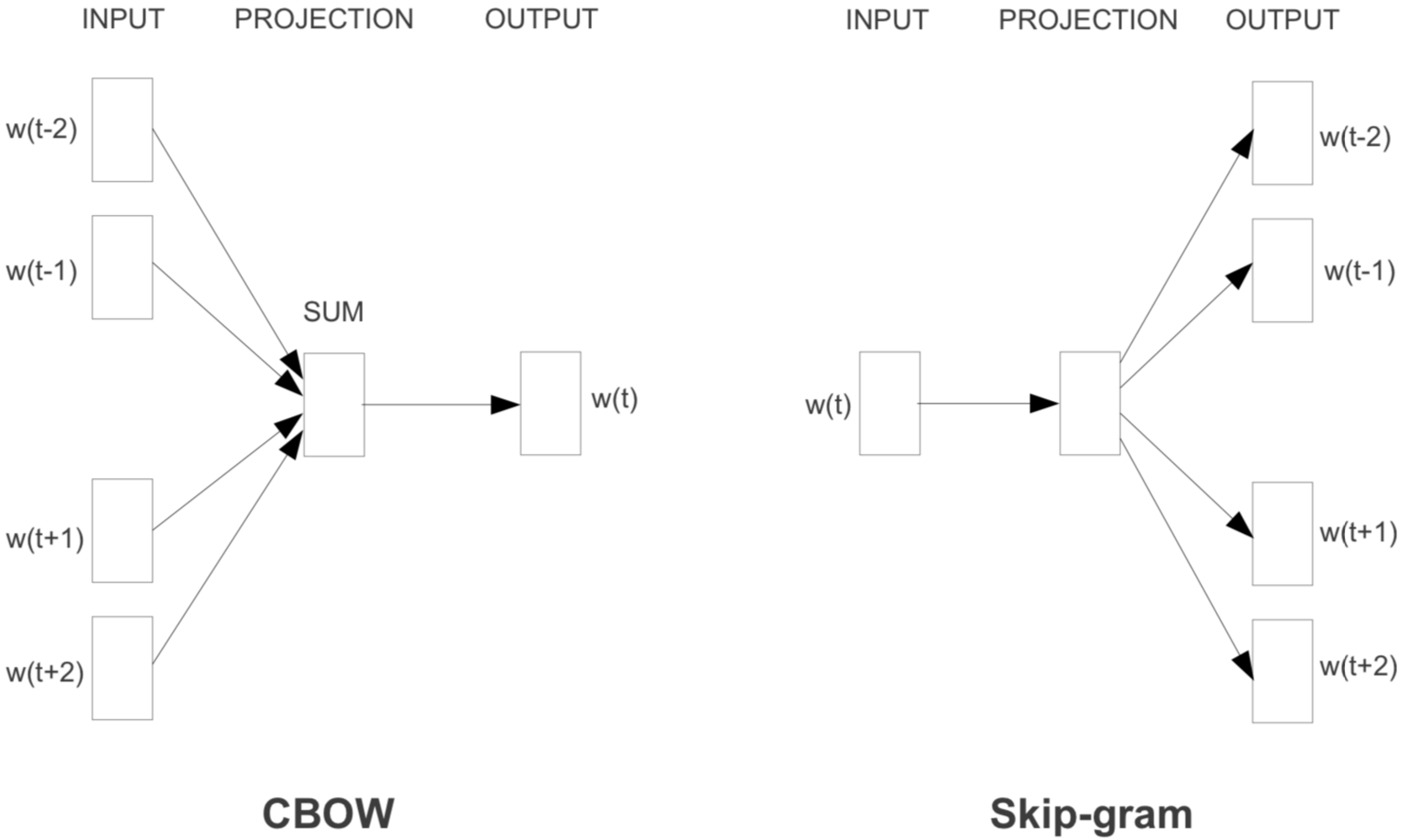
- Start with random vectors
- Iterate through each word position in the whole corpus
- Try to predict surrounding words using word vectors $P(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w \in V} \exp(u_w^T v_c)}$



- Learning: update vectors so they can predict actual surrounding words better
- The word embedding model try to learn word vectors that capture well word similarity and meaningful directions in a word space!

Word2vec maximizes objective function by putting similar words nearby in space

Two variant approaches for word2vec



Skip-gram vs. CBOW

- Skip-gram
  - Predict context (‘outside’) words (position independent) given center word
- CBOW
  - Predict center word from (bag of) context words

Skip-gram

- Current word is used as input to a log-linear classifier
- Predict words within certain range before and after of this current word
- The normalization term is computationally expensive as:

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

A big sum over words

- Skip gram model is typically implemented with “**negative sampling**”

Skip-gram with negative sampling

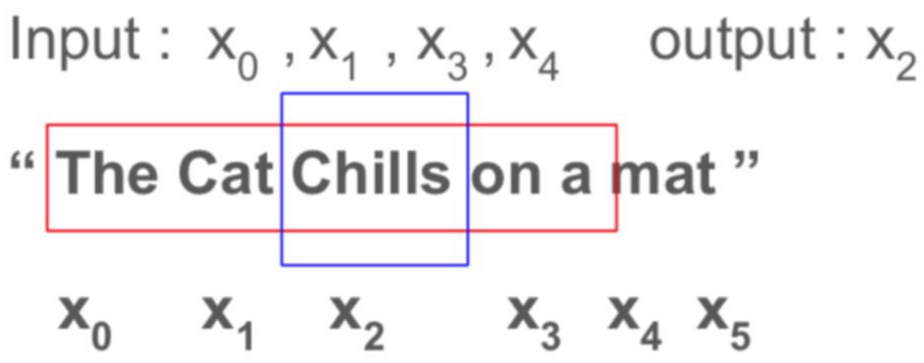
- Main idea: train binary logistic regression to differentiate a true pair (center word and a word in its context window) versus some "noise" pairs (the center word paired with a random word)
- Maximize the objective function:

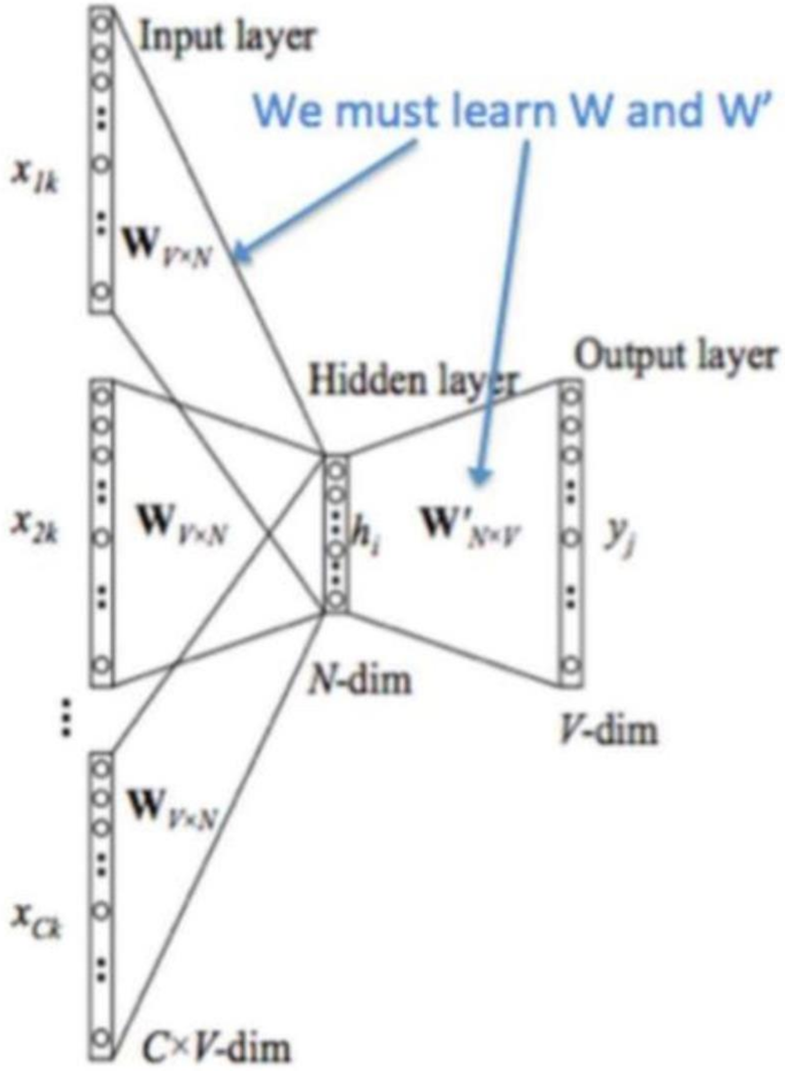
$$J_t(\theta) = \log \sigma\left(u_o^T v_c\right) + \sum_{i=1}^{k} \mathbb{E}_{j \sim P(w)}\left[\log \sigma\left(-u_j^T v_c\right)\right]$$

- We take k negative samples, maximize the probability that real outside word appears, minimize the probability that random words appear around center word

CBOW (Continuous BOW) (1)

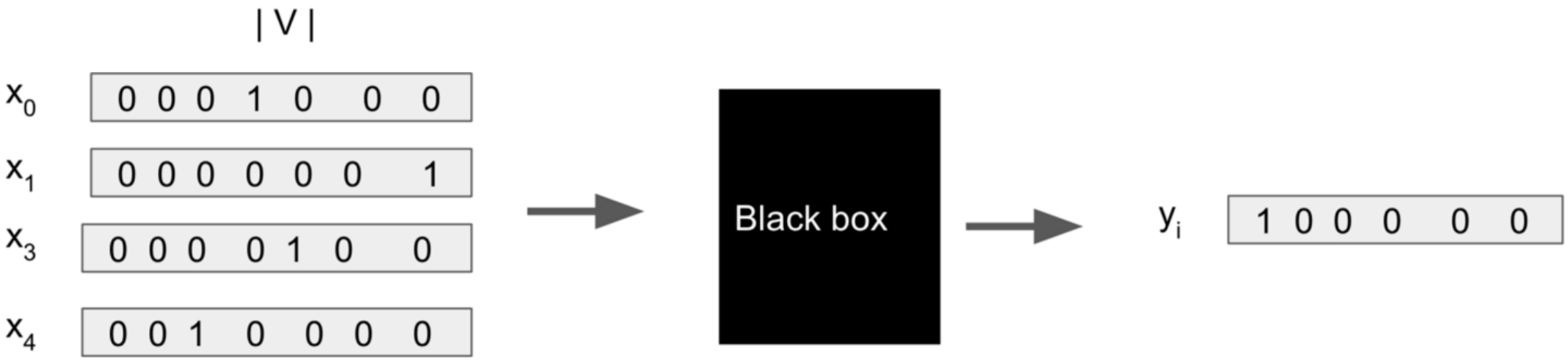
- Predict a word using context





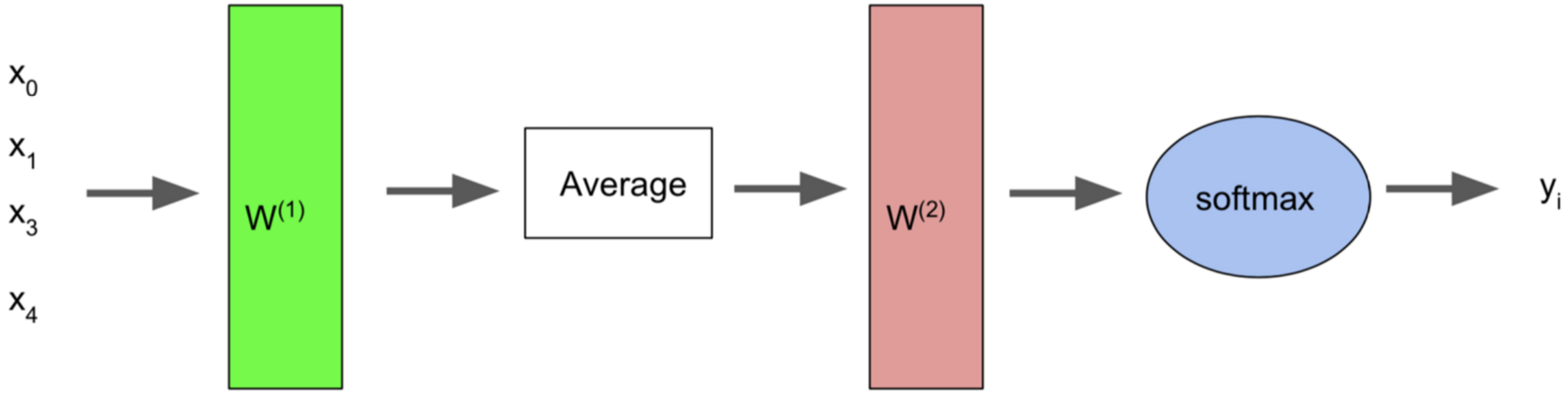
CBOW (2)

- |V| is the size of the vocabulary corpus
- x_i represents the one-hot vector of the i^{th} word
- y_i represents the one-hot vector of the expected word



CBOW (3)

- $|V|$ is the size of the vocabulary corpus
- x_i represents the one-hot vector of the i^{th} word
- y_i represents the one-hot vector of the expected word



CBOW (4)

y_i	1 0 0 0 0 0 0 0
Z	32 14 23 0.22 2 14 55 19
y^	0.7 0.1 0.02 0.08 0 0 0.1

y^ = softmax (Z)

$$\sigma(\mathbf{z})_j = \frac{e^{z_j}}{\sum_{k=1}^{K} e^{z_k}}$$

$y_i \in R^{|V| \times 1}$ is the one-hot vector of the expected word

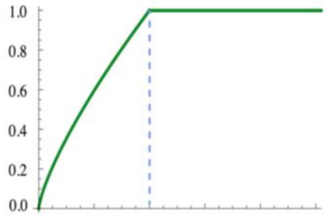
GLOVE – Global vector for word representation

- 2 assumptions:
  - Global context (global matrix factorization)
    - Co-occurrence of words through documents
  - Local context
    - A pre-fixed size slide window
- Idea: Encoding meaning components in vector differences

A: Log-bilinear model: $w_i \cdot w_j = \log P(i|j)$

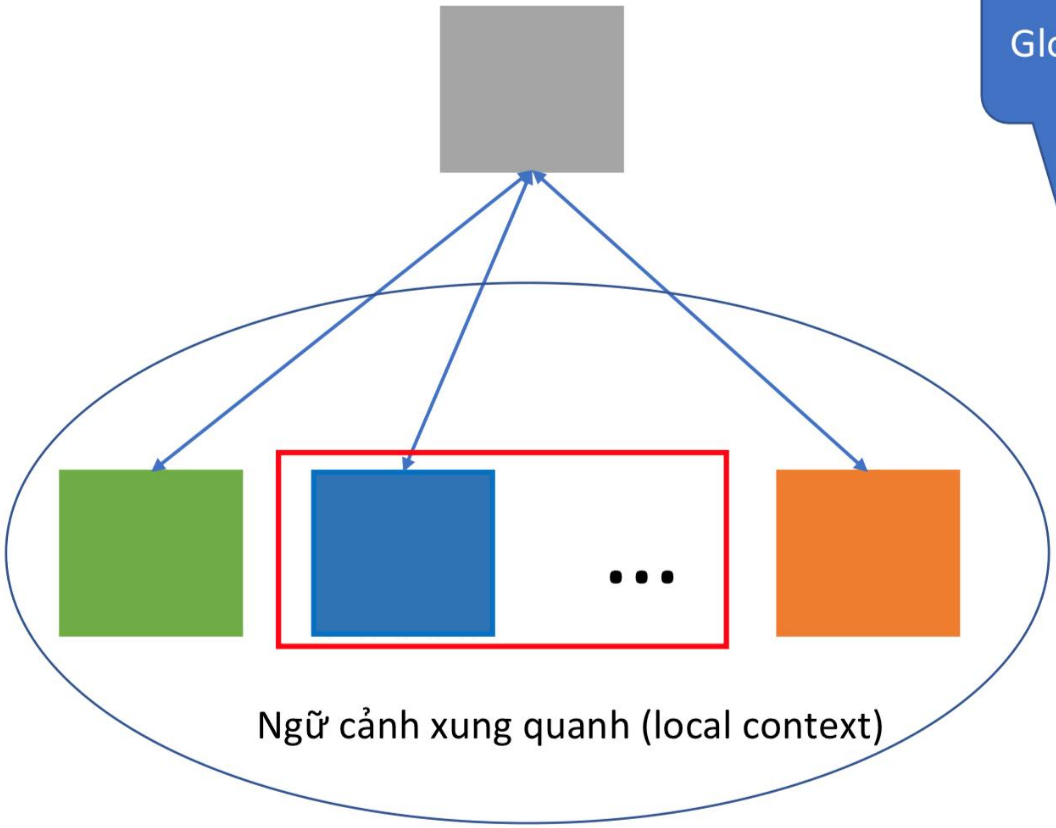
with vector differences $w_x \cdot (w_a - w_b) = \log \frac{P(x|a)}{P(x|b)}$

Loss: $J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$

$f \sim$ 

- Fast training
- Scalable to huge corpora

Word2Vec vs. Glove



Global context

Local context

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

Ma trận đồng xuất hiện

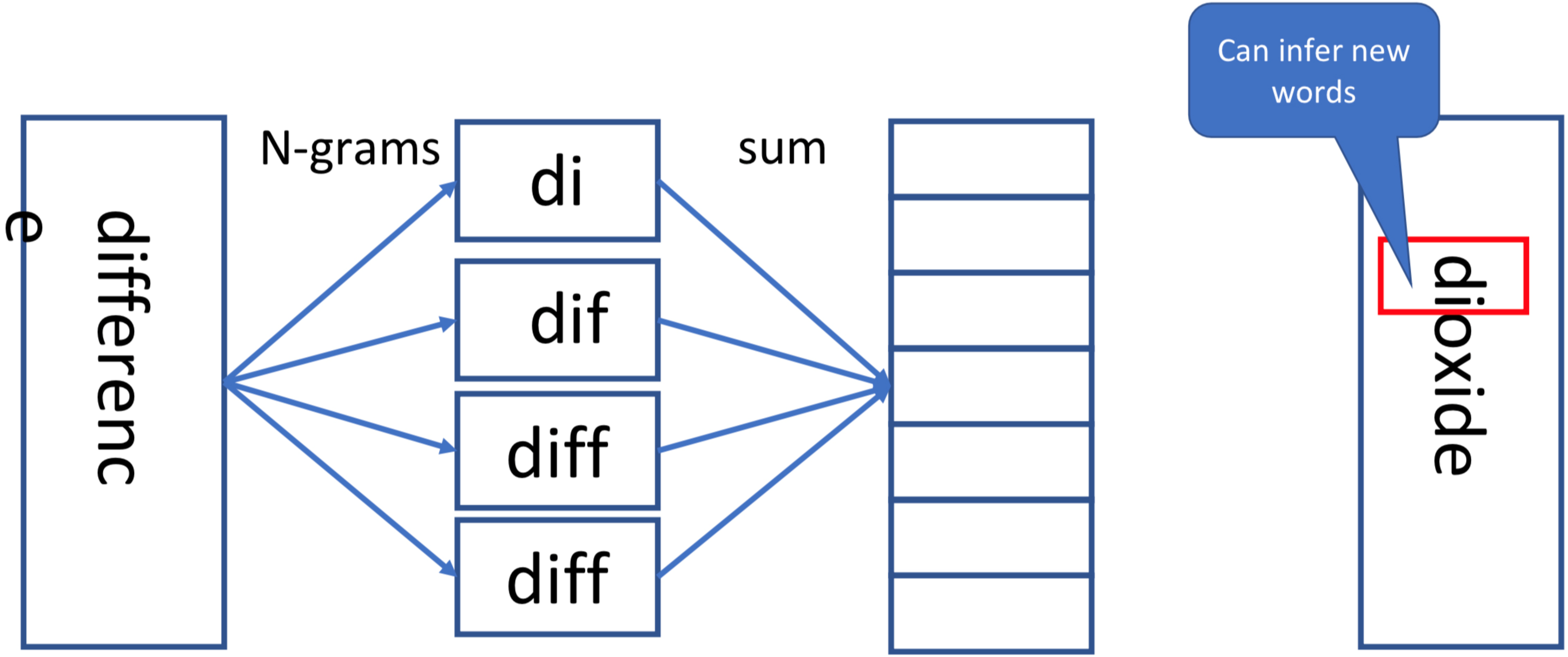
Pros and cons

- Pros:
  - Fast training
  - Well scaled on big corpus data
  - Work well on small data
  - Early stopping
- Cons
  - Memory consuming
  - Learning rate may affect the accuracy of the model

Fast Text

- An extension of Word2vec
- Facebook
- Multi-language support
- Sub-word
  - Based on n-grams model
  - Allow to short word learning
  - Allow to represent prefixes and postfixes of word
- Work well with rare-words

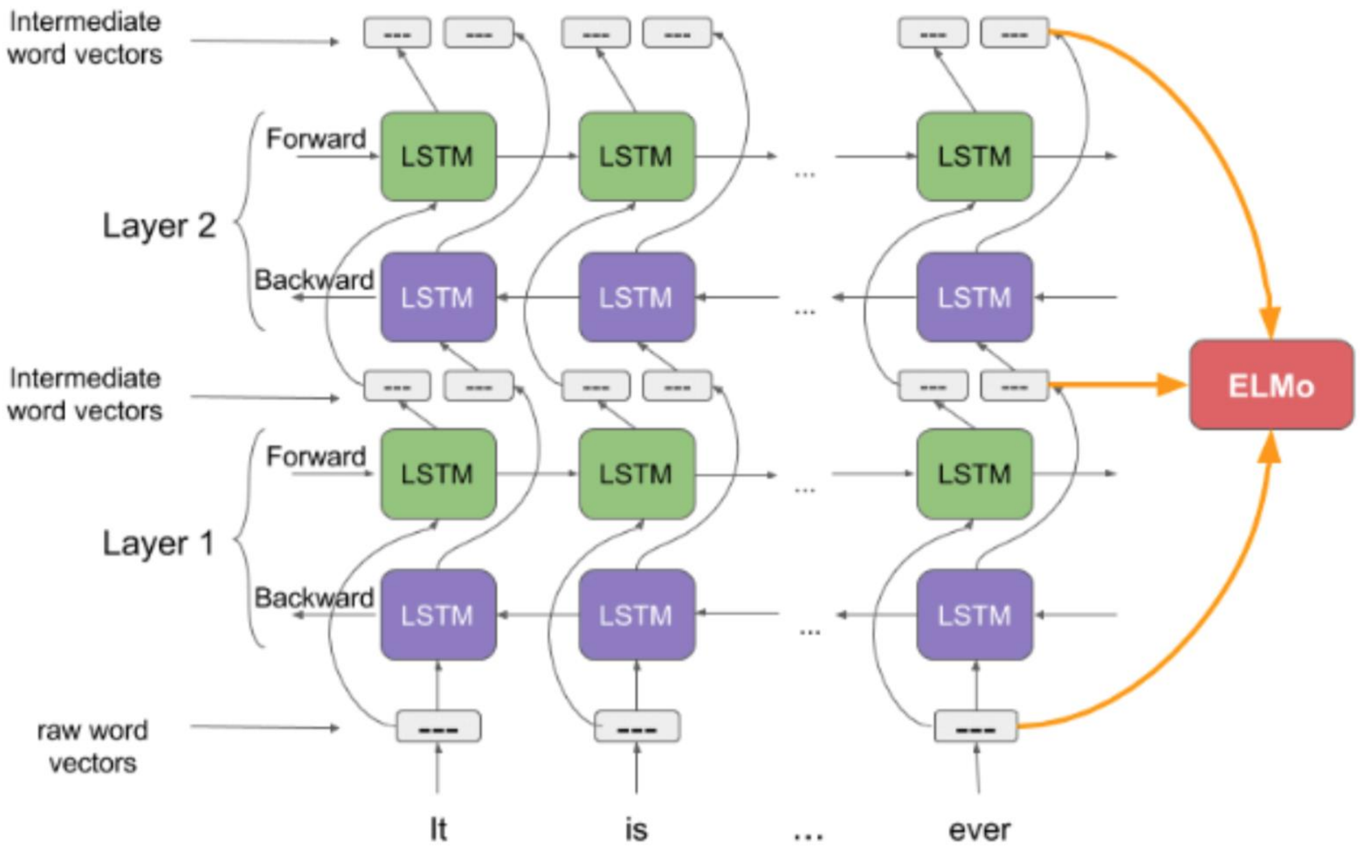
Word vector of Fast text



Pros and cons

- Capture rare-words thanks to sub-word representation
- Memory consuming for sub-word representations

ELMo – Embedding from Language Model



https://www.analyticsvidhya.com/blog/2019/03/learn-to-use-elmo-to-extract-features-from-text/

ELMo - Architecture

- Using character-level CNN to represent word (raw word vectors)
- Bi-directional LSTM
- Combine forward and backward directions to represent intermediate word vectors
- Second layer using intermediate word vectors as input with the same architecture as first layer
- Final word vector:
  - Combine first representation (raw word vector) and two outputs of two layers – ELMo vector

Pros and cons

- Better capture the context of word than word2vec and Glove

I ***read*** the book yesterday vs. Can you ***read*** the letter now?

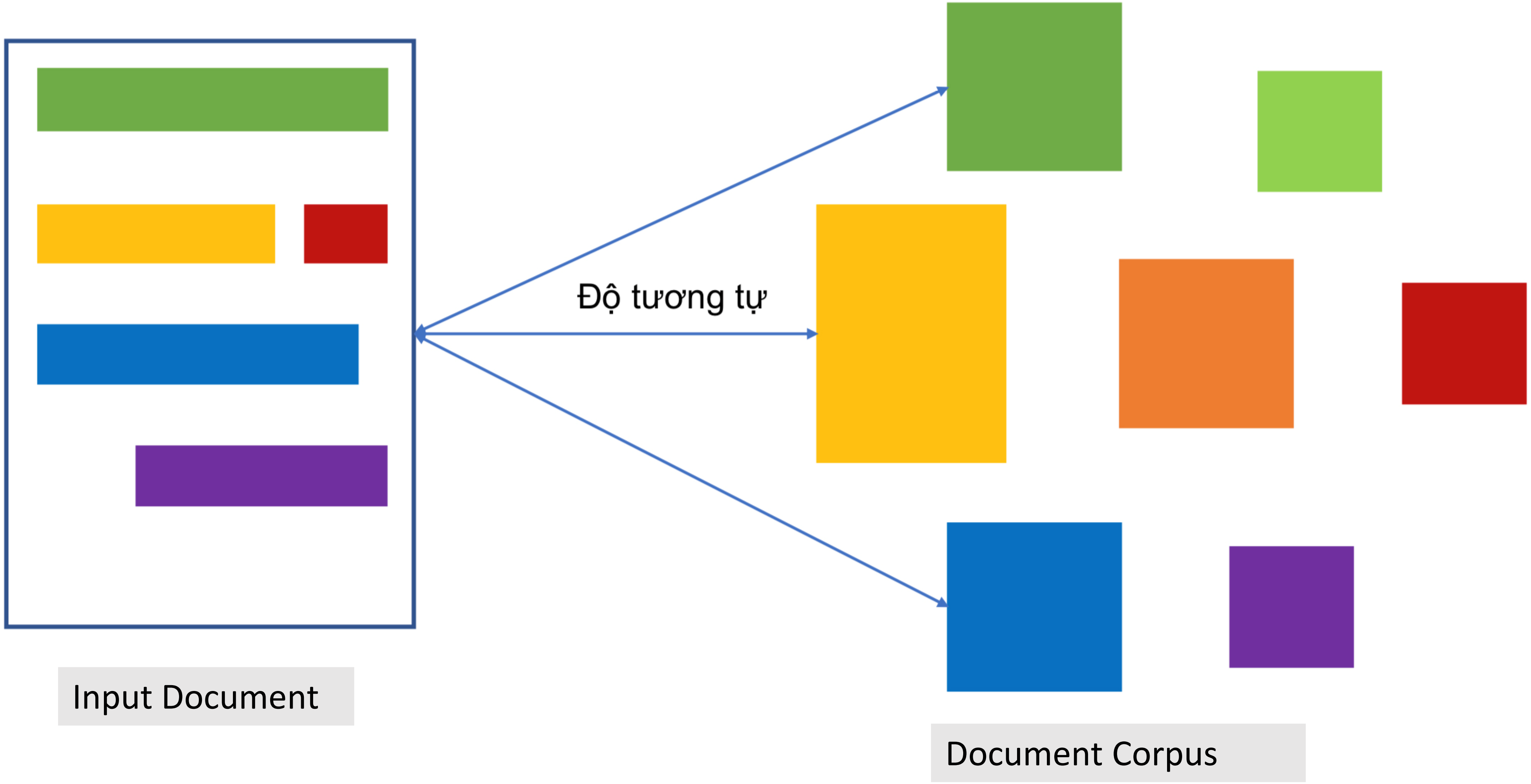
- The same words may have the different representation depending on the context
- Rare-word representation (as Fast Text)
- Memory consuming

Building word vector model

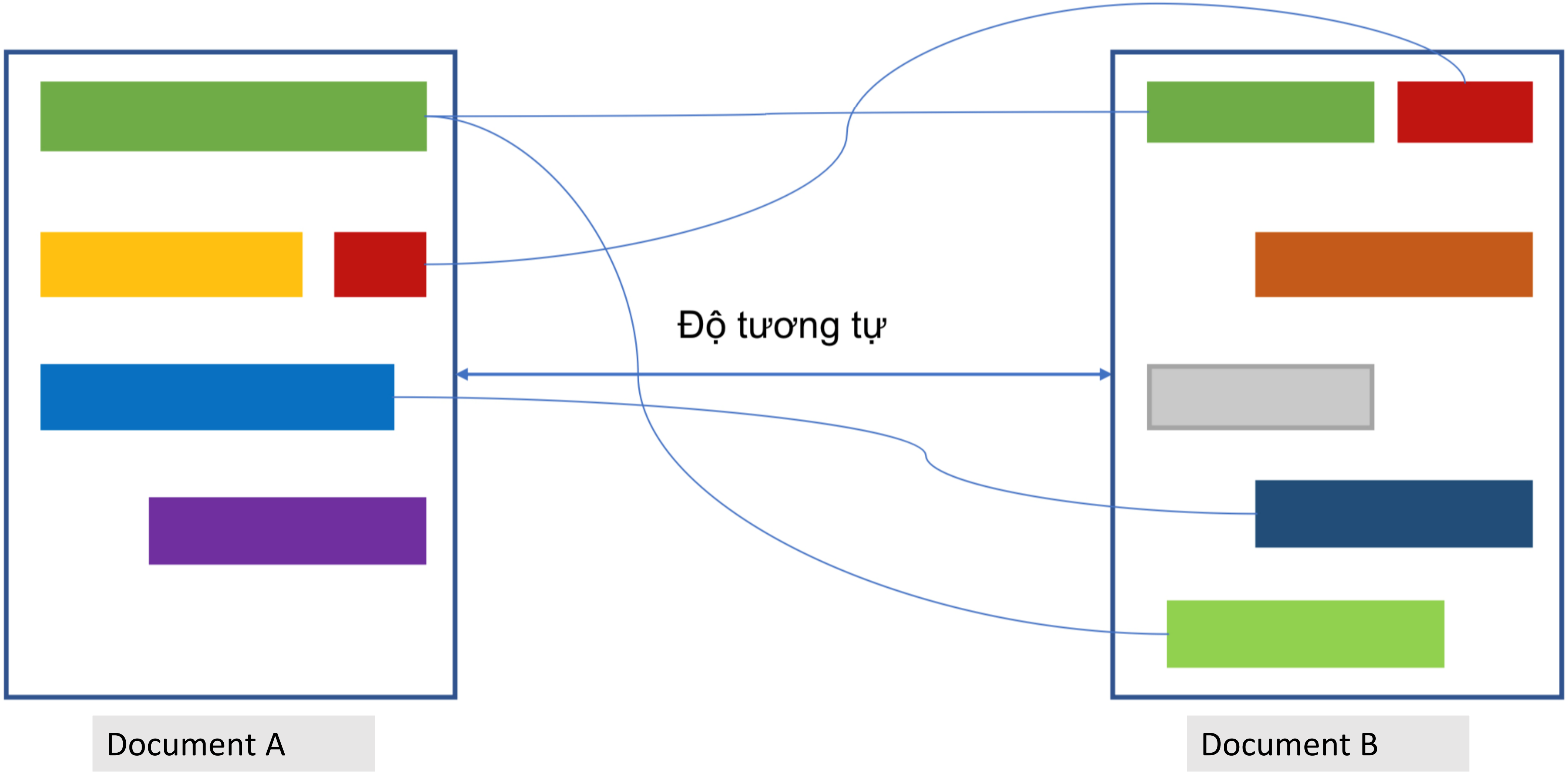
- A large text corpus
  - Wikipedia
- Choose an appropriate model
- Training model
- Using the model to solve problems of NLP

Application - Plagiarism Detection

Problem of Plagiarism Detection



Similarity Comparison



Challenges

- Comparing the similarity of different parts between two documents is much more difficult
- Long document
- Structure and vocabulary
- Focus on semantics and syntactics

Summary

- Text Vectorization
- Word Embedding
- Word Embedding models
  - Word2vec
  - Glove
  - Fast Text
  - EMLo
- Building a model for word representation