Convolutional Neural Networks for Sentence Classification

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Definition of NLP

Tokenizing

Embedding

Definition of NLP

How to program computers
to **process** and **analyze**
of natural language data.

0. Basic NLP

Tokenizing

Time is not gold, but it is yourself.

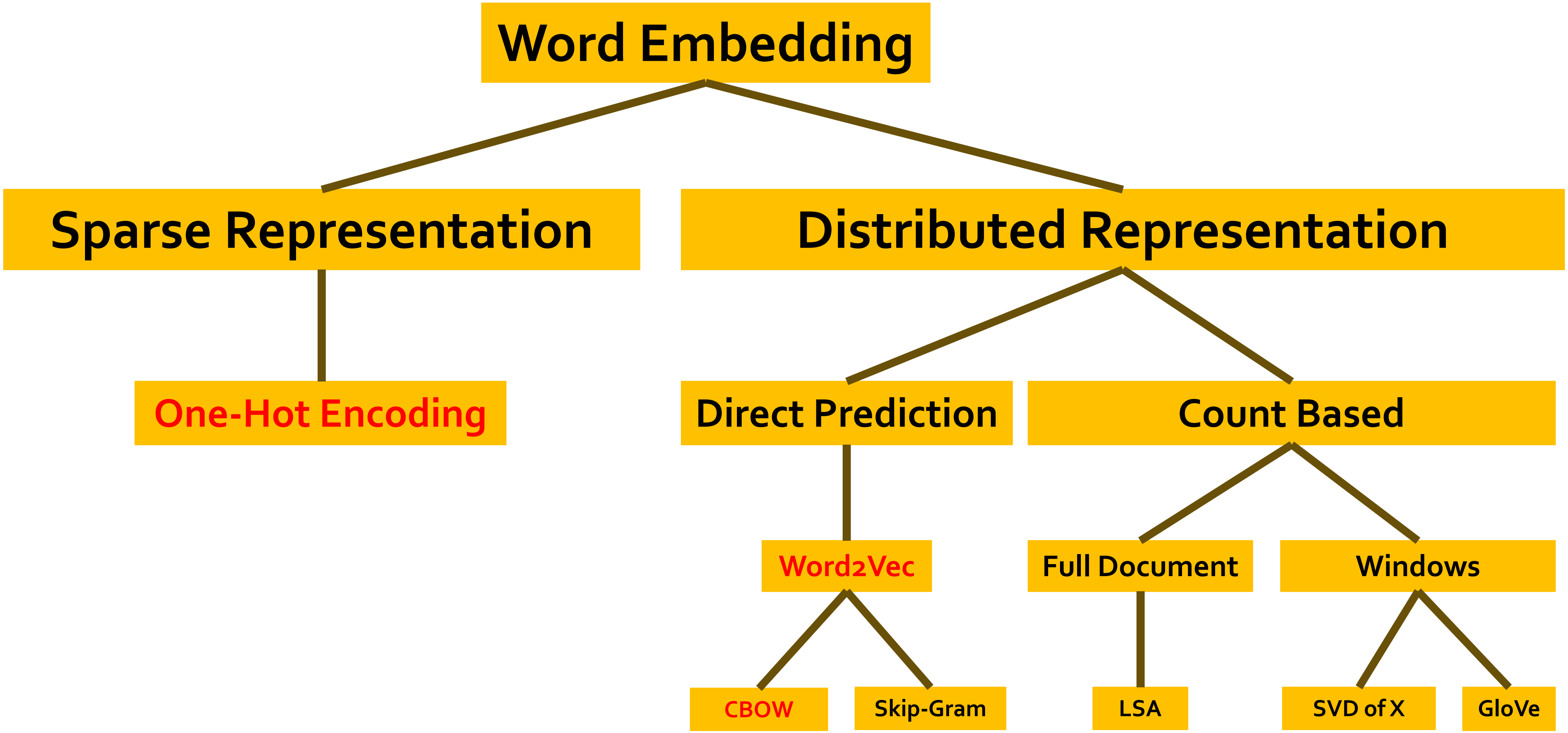
- Alphabet : “T”, “i”, “m”, “e”, “s”, “n”, “o”, “t”, “g”, “l”, “d”, “b”, “u”, “f”
- Word : “Time”, “is”, “not”, “gold”, “but”, “it”, “yourself”
- Sentence : “Time is not gold, but it is yourself.”

0. Basic NLP

Word Embedding

- **Word Representation** to make machine understand Natural Language.
- **Vector representations** of a particular word

0. Basic NLP


Word Embedding
Sparse Representation
Distributed Representation
One-Hot Encoding
Direct Prediction
Count Based
Word2Vec
Full Document
Windows
CBOW
Skip-Gram
LSA
SVD of X
GloVe

0. Basic NLP

One-hot-encoding

- "Time" : [1, 0, 0, 0, 0, 0, 0]
- "is" : [0, 1, 0, 0, 0, 0, 0]
- "not" : [0, 0, 1, 0, 0, 0, 0]
- "gold" : [0, 0, 0, 1, 0, 0, 0]
- "but" : [0, 0, 0, 0, 1, 0, 0]
- "it" : [0, 0, 0, 0, 0, 1, 0]
- "yourself" : [0, 0, 0, 0, 0, 0, 1]

One-hot-encoding

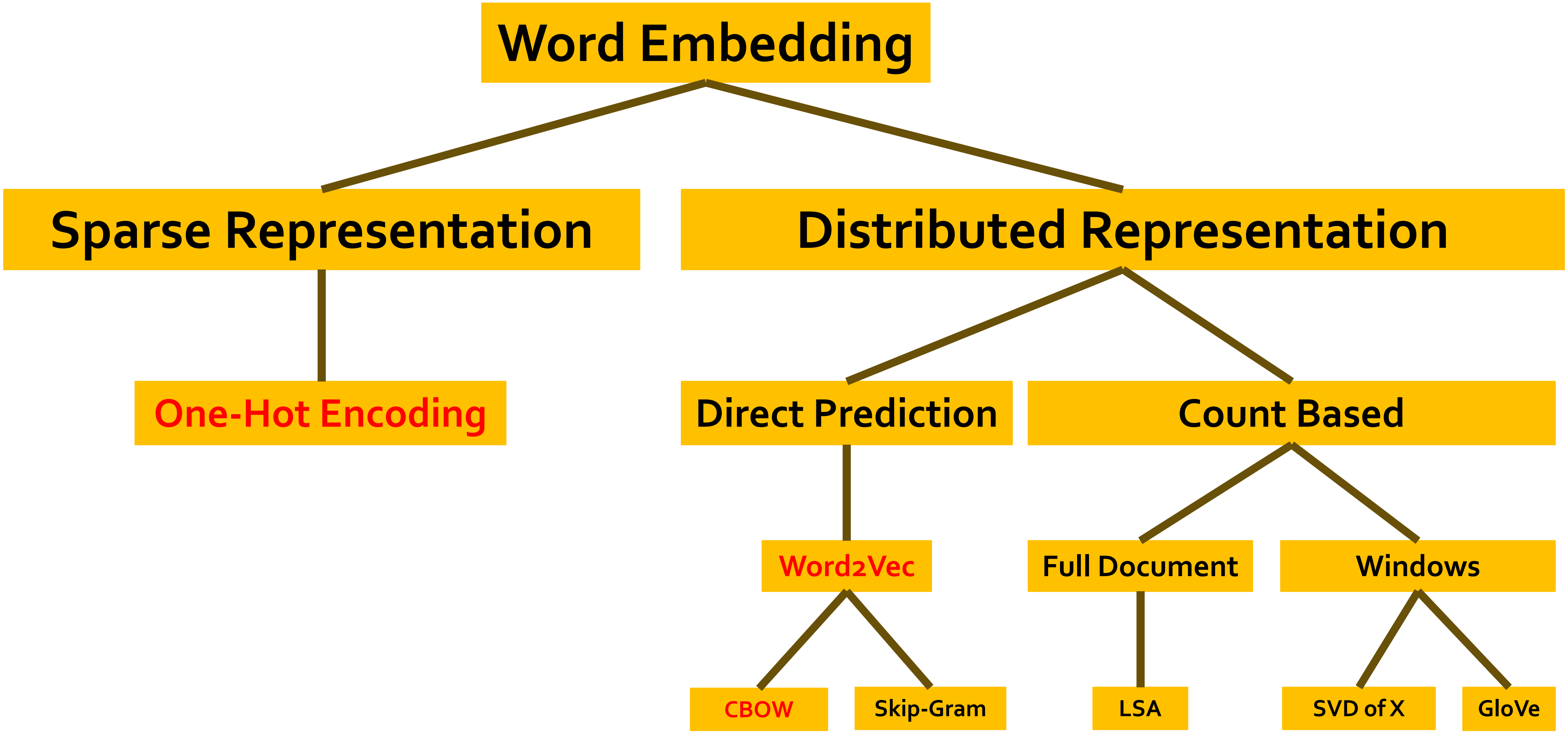
- "Time" : [1, 0, 0, 0, 0, 0, 0]
- "is" : [0, 1, 0, 0, 0, 0, 0]
- "not" : [0, 0, 1, 0, 0, 0, 0]
- "gold" : [0, 0, 0, 1, 0, 0, 0]
- "but" : [0, 0, 0, 0, 1, 0, 0]
- "it" : [0, 0, 0, 0, 0, 1, 0]
- "yourself" : [0, 0, 0, 0, 0, 0, 1]

Sparse

&

It can't represent mean of words.

0. Basic NLP



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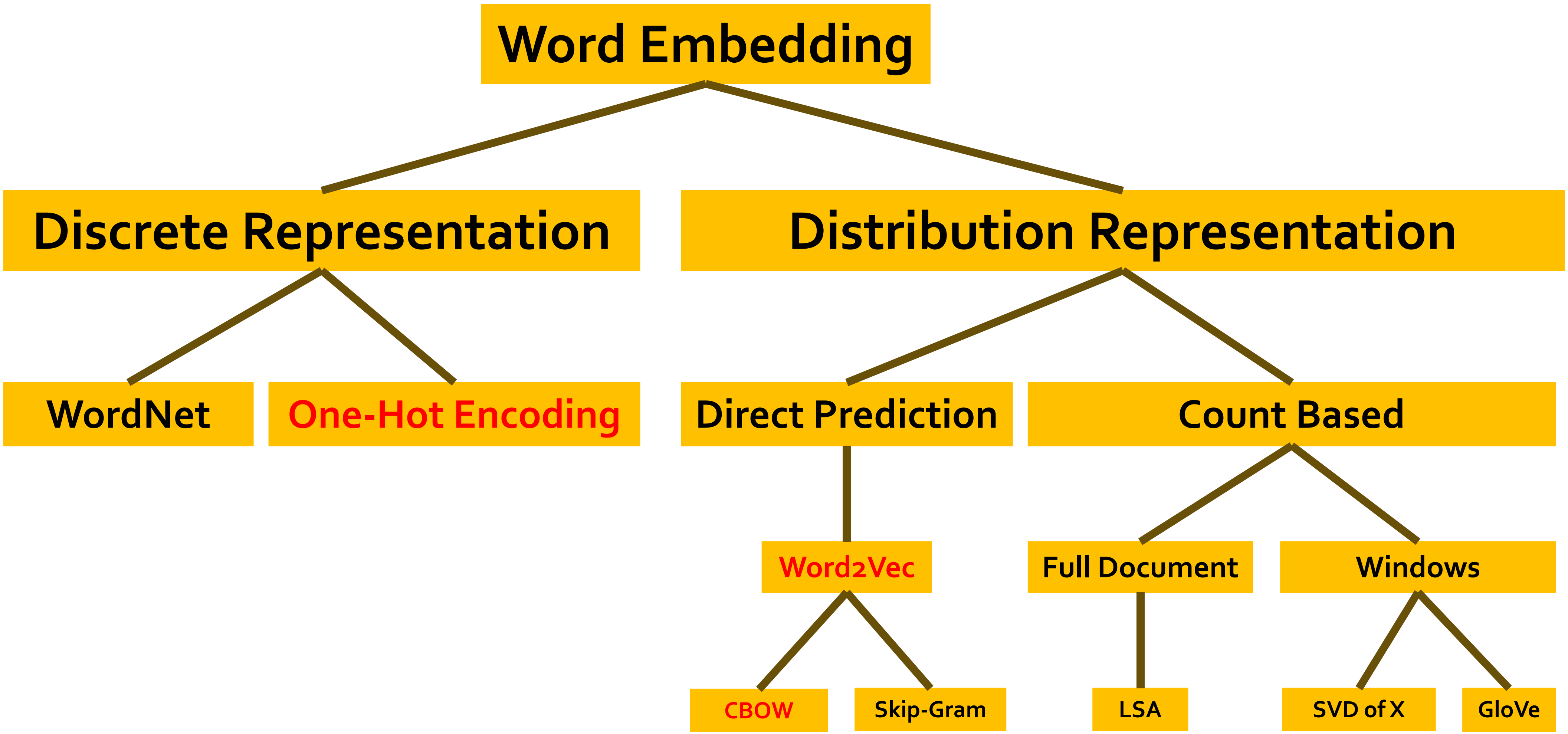
0. Basic NLP


Word Embedding
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Distribution Representation
WordNet
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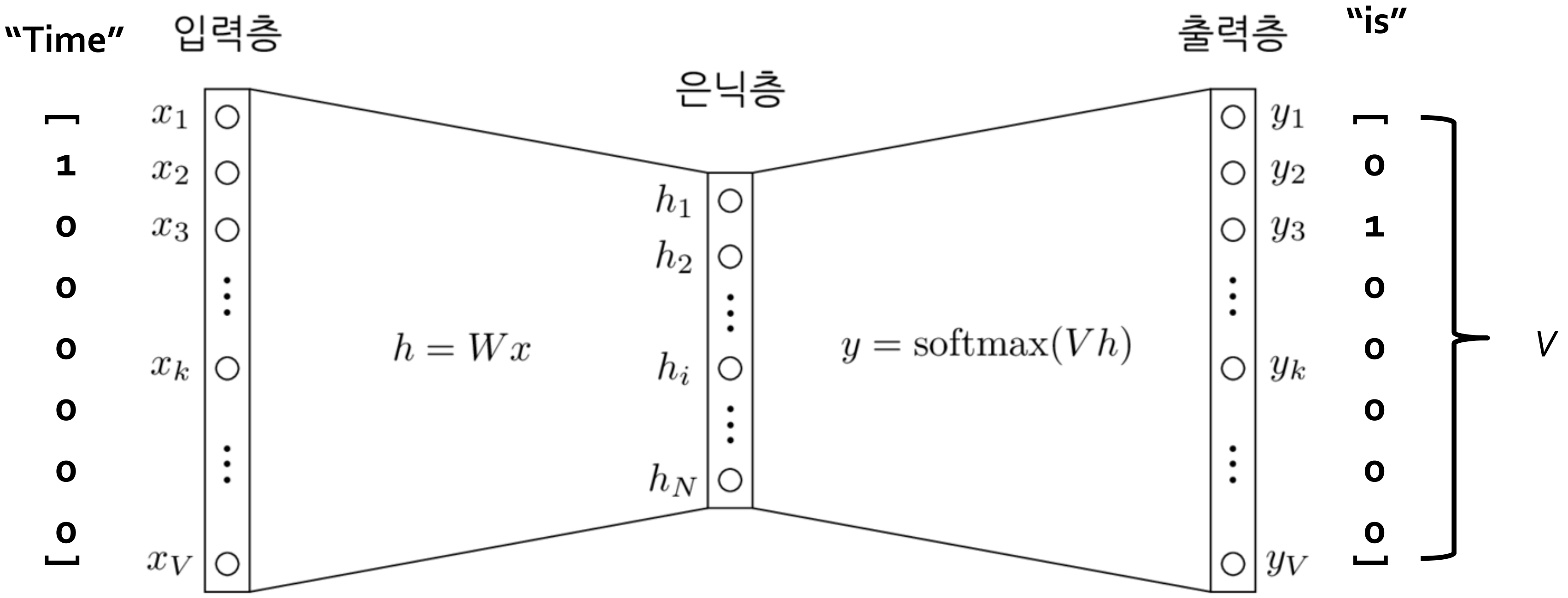
0. Basic NLP

Word2Vec : (0) Basic

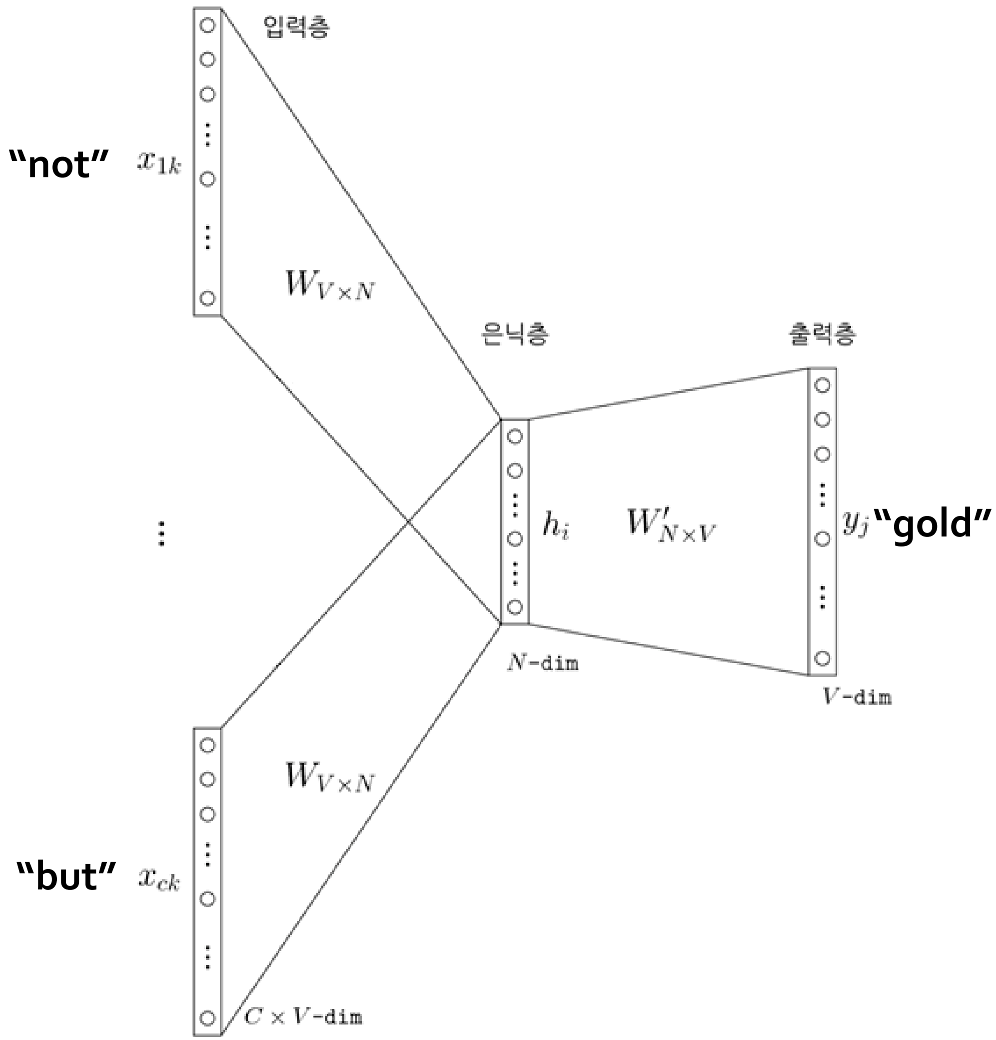


0. Basic NLP

Word2Vec : (1) CBOW

Time is not ____ but it is yourself

W = 1 (window size)

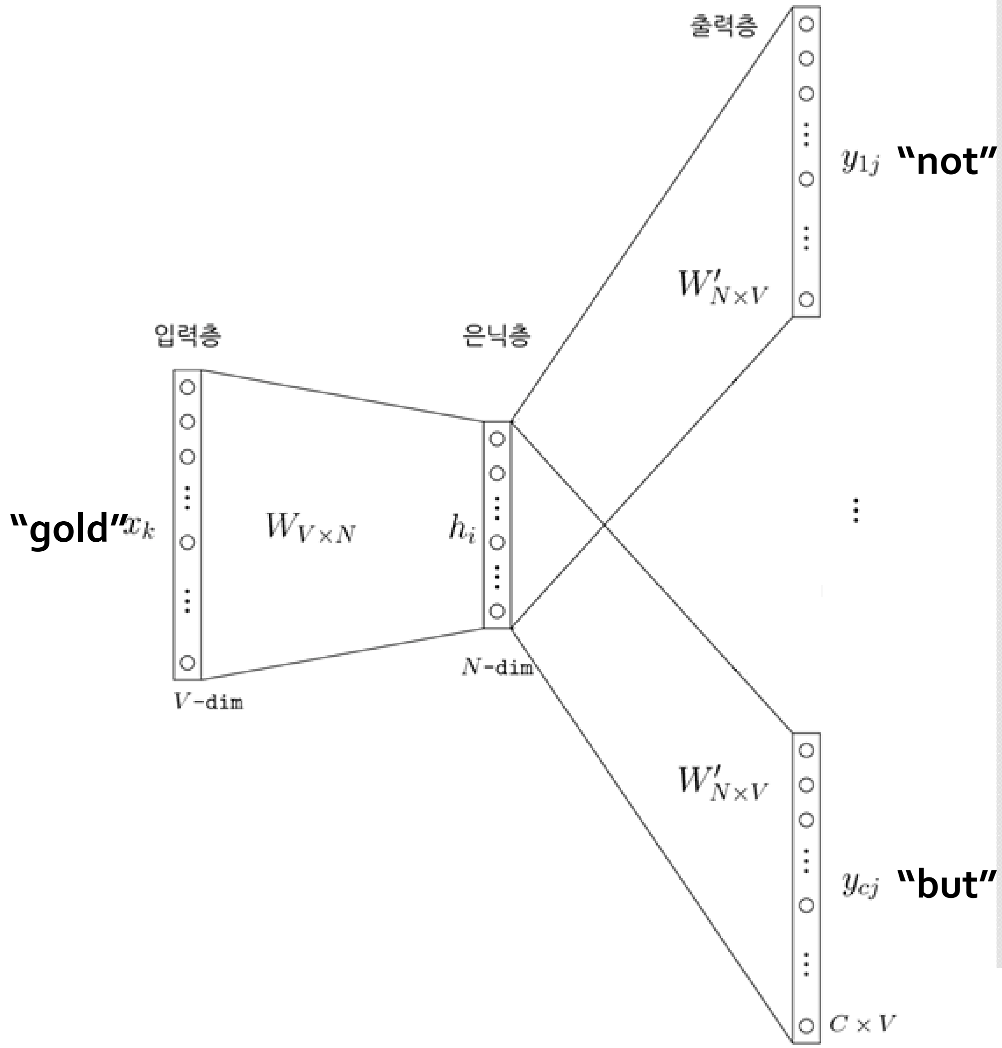


0. Basic NLP

Word2Vec : (2) Skip-gram

Time is ___ gold ___ it is yourself

W = 1 (window size)

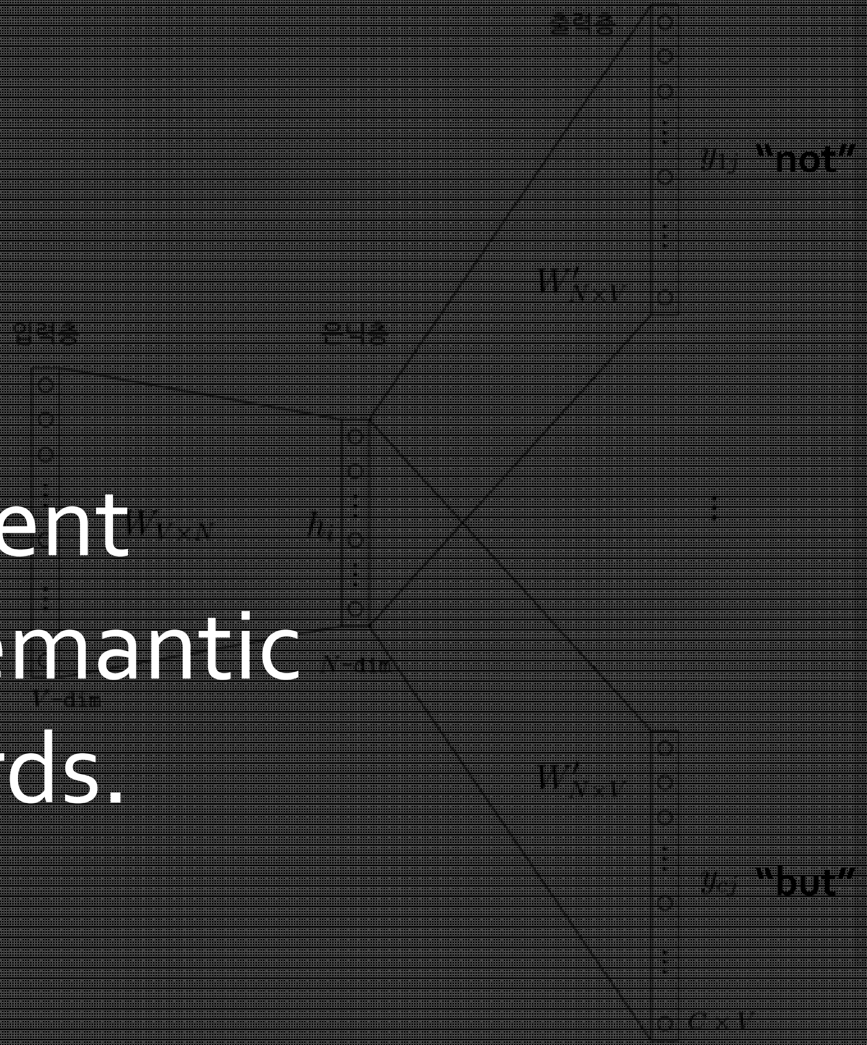


0. Basic NLP

Word2Vec : (2) Skip-gram

Time is ___ gold ___ it is

W = 1 (window size)



Dense

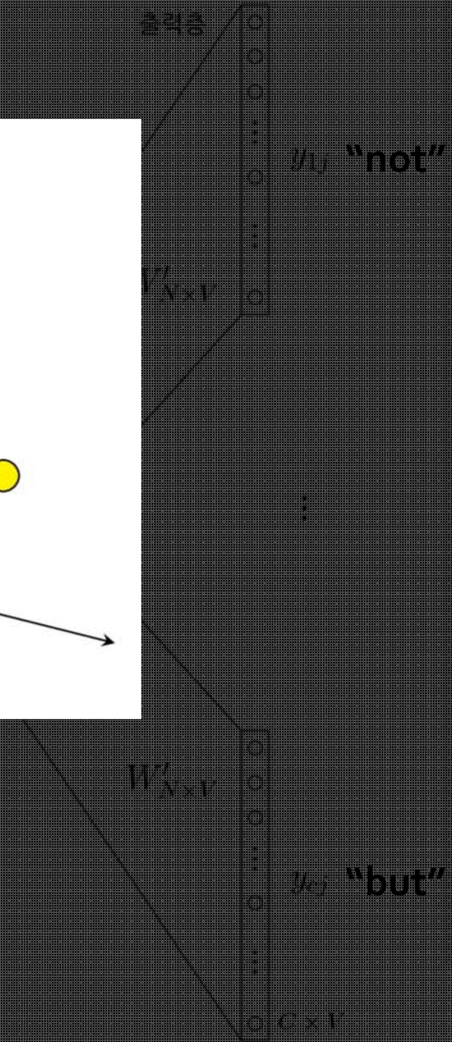
&

It can represent

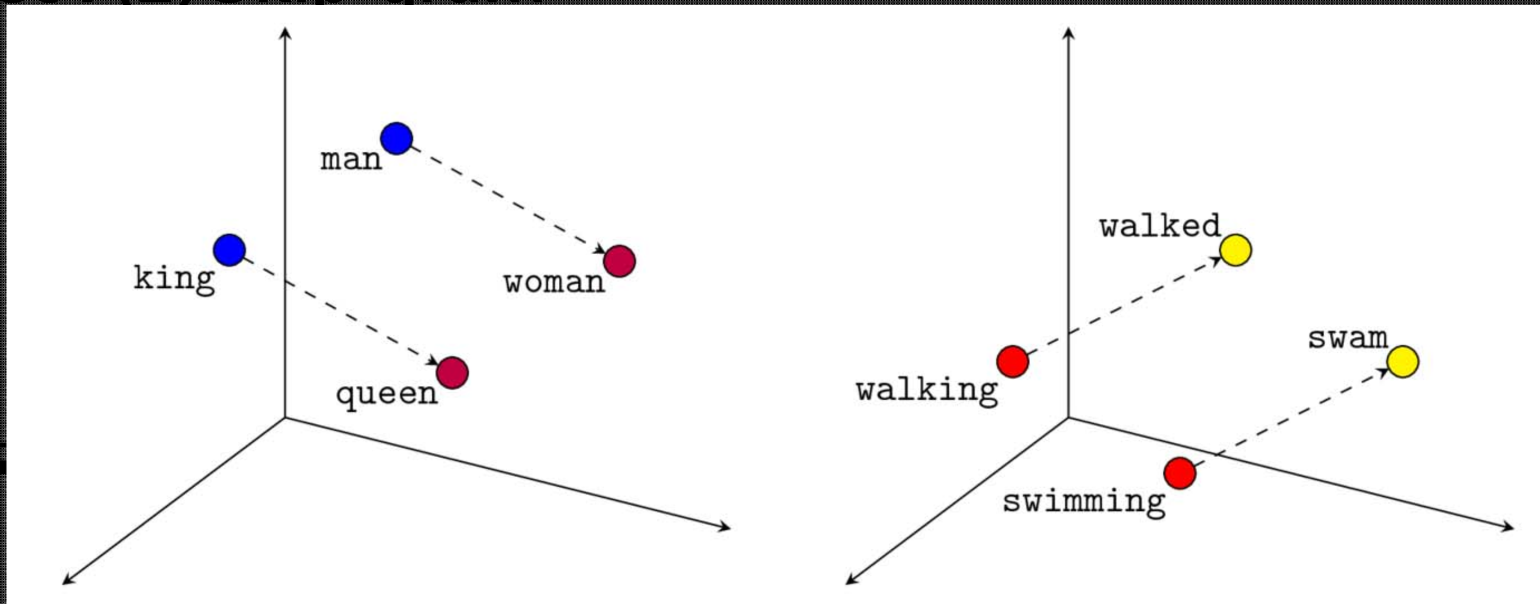
Semantic and Semantic

mean of words.

Word2Vec : (2) Skip-gram



Time is _



W = 1 (window size)

Semantic & Synthetic mean of words.

1. Introduction

Background of this paper

(1) Much of NLP work with deep-learning is based on

Word Embedding represented by Neural Language Model

(2) **CNN** have been shown to be **effective** for **NLP** too.

(3) In Image Classification, **pre-trained** **feature extractors perform well** on a variety of tasks (Razavian et al. , 2014).

1. Introduction

Background of this paper

What if

we design the NLP model

with CNN

and Pre-trained word vector?

2. Model

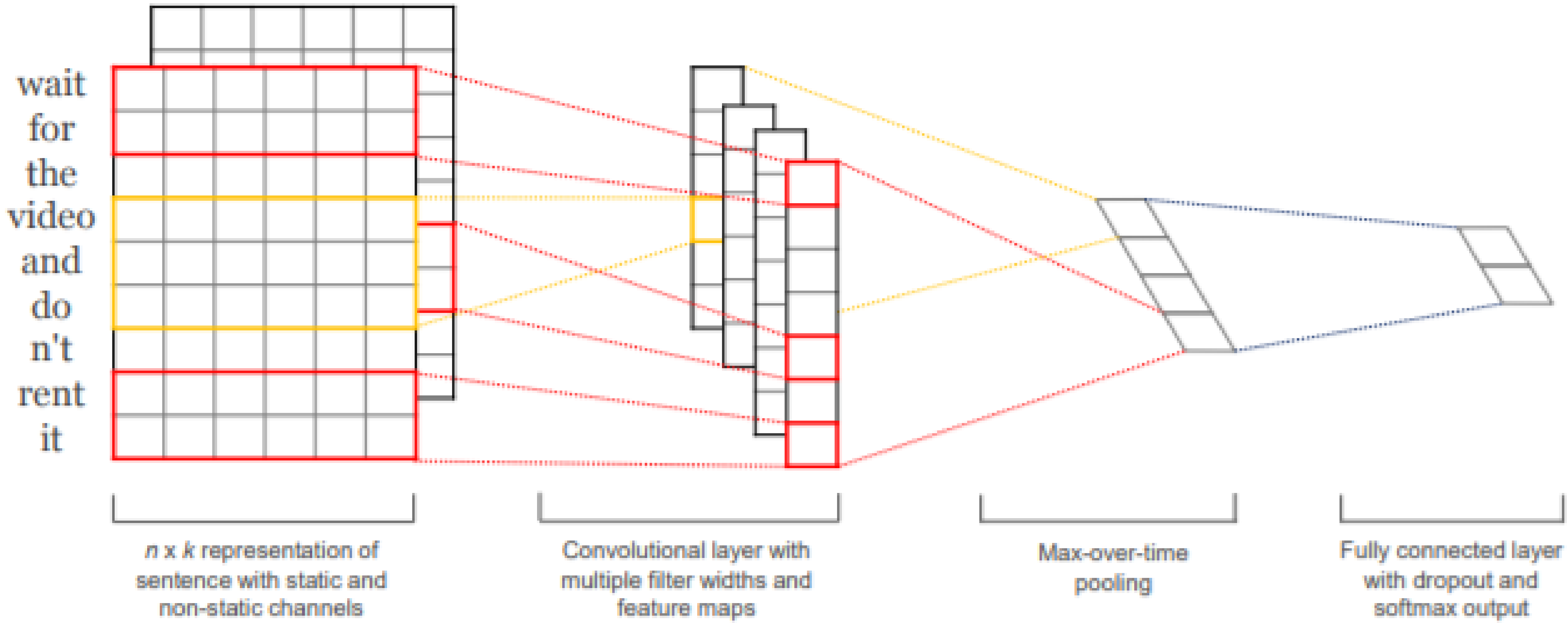
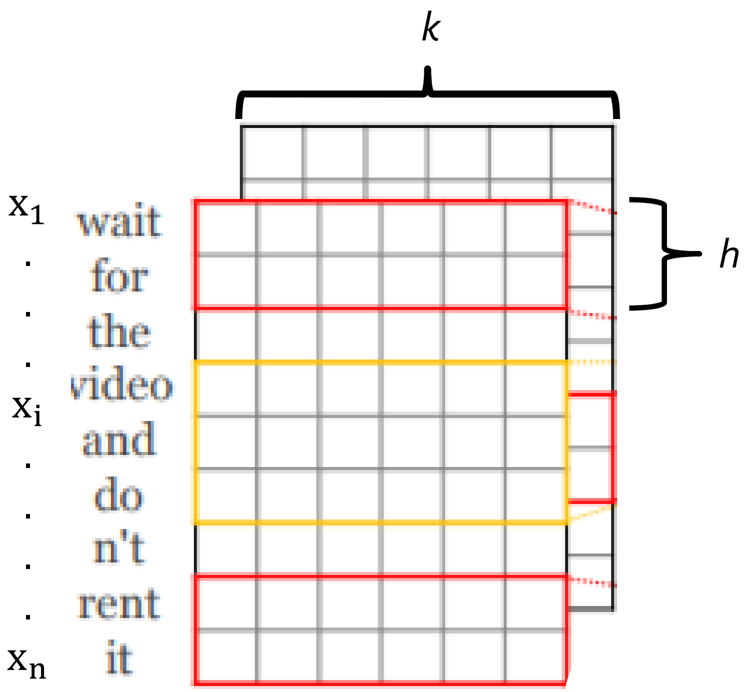


Figure 1: Model architecture with two channels for an example sentence.

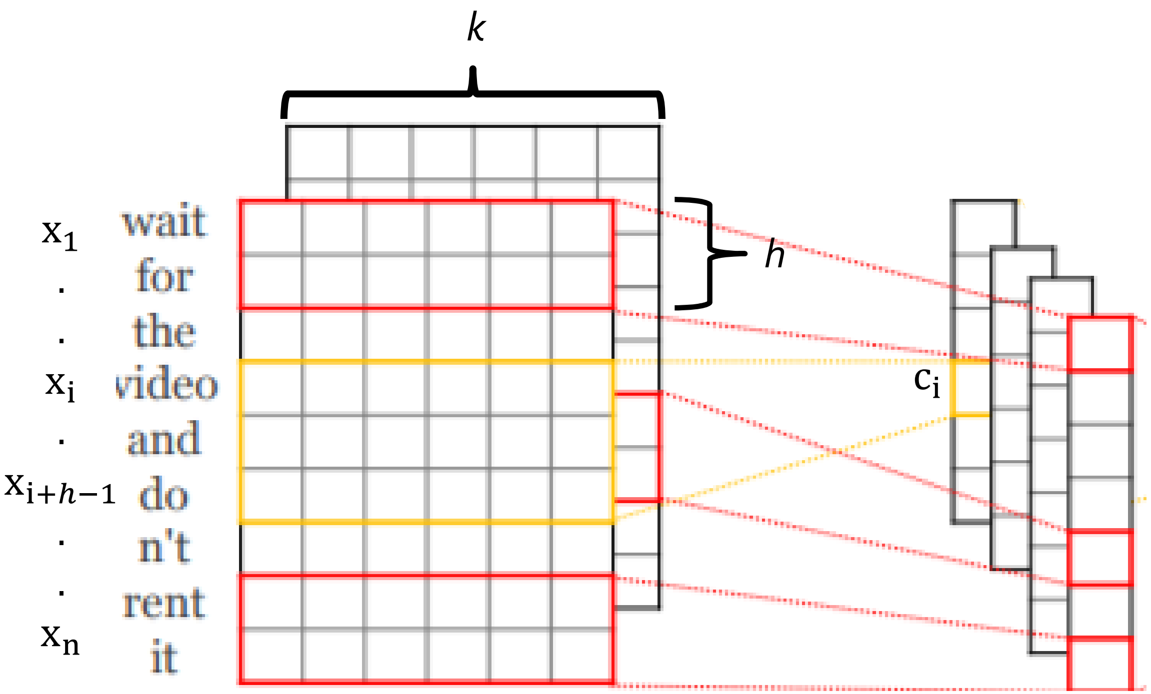
2. Model

Model Architecture
(1) Representation of Sentence



2. Model

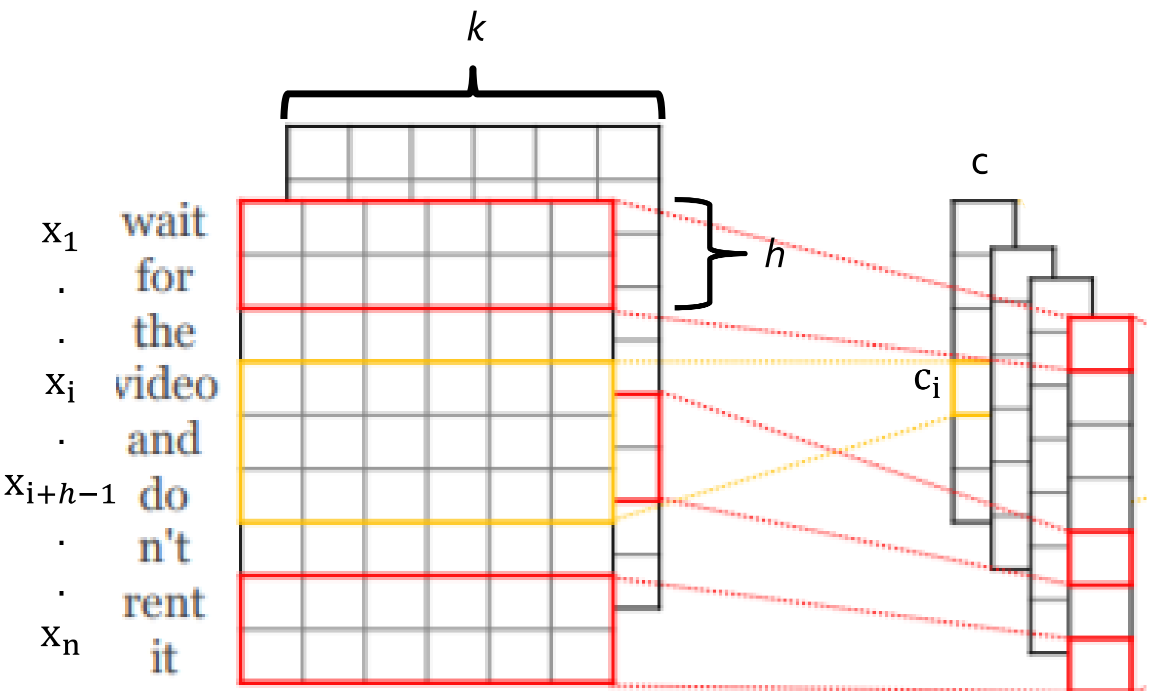
Model Architecture
(2) Convolution Operation



$$c_i = f(\mathrm{w} \cdot \mathrm{x}_{\mathrm{i:i+h-1}} + \mathrm{b})$$

2. Model

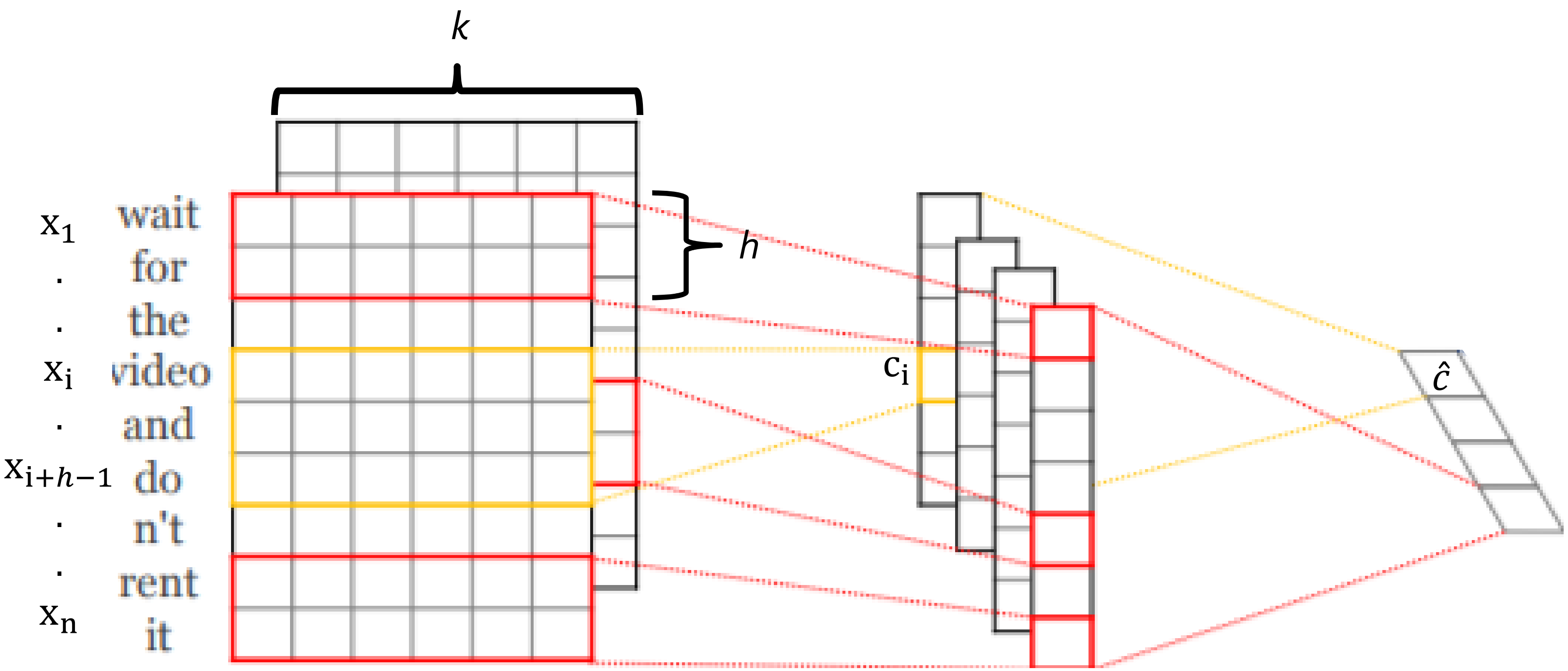
Model Architecture
(3) Feature map



$$c = [c_1, c_2, \dots c_i, \dots, c_{n-h+1}]$$

2. Model

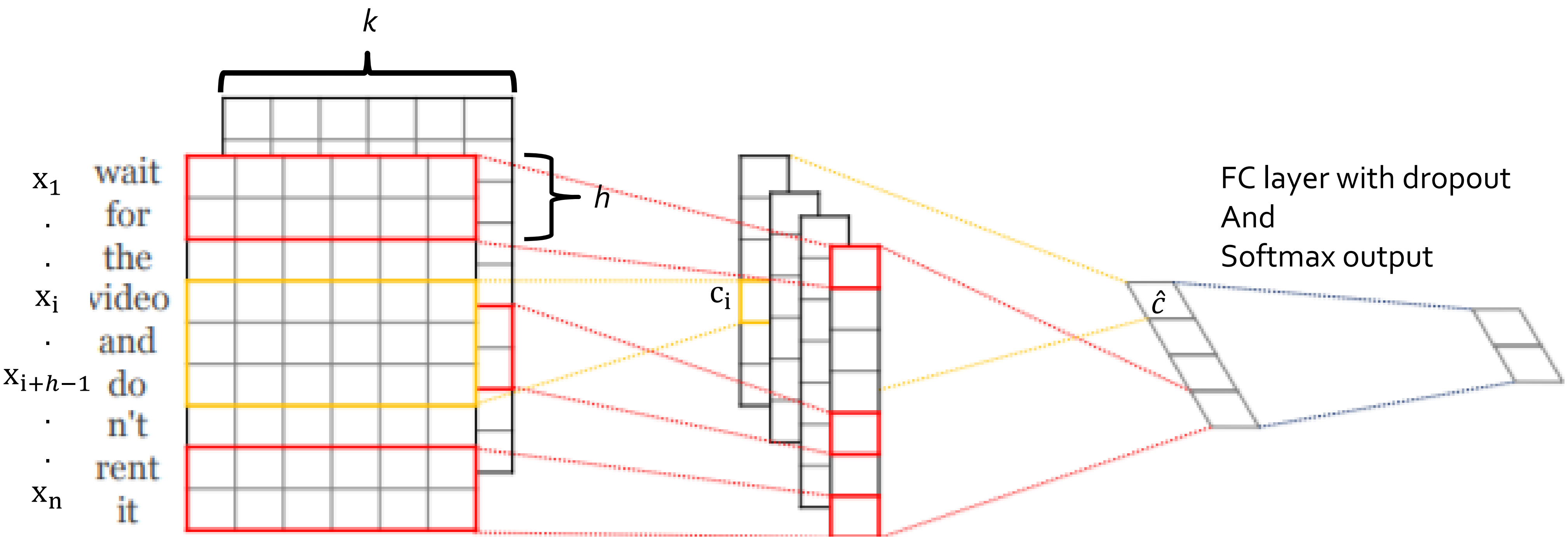
Model Architecture
(4) Max-over-time pooling



$$\hat{c} = \max\{c\}$$

2. Model

Model Architecture
(5) Dropout and Softmax output



2. Model

1. Regularization

1. Dropout

2. constraint on l_2 - norms of weight vectors

3. Data and Experimental setup

- MR : Movie reviews(pos / neg)
- SST-1 : vpos / pos / neu / neg / vneg
- SST-2 : Same as MR

- Subj : Sub / Obj
- TREC : Classifying a Q into 6 Q types(person, location, etc.)
- CR : Customer Reviews of product (pos / neg)
- MPQA : Opinion polarity detection.

Data	c	l	N	$\|V\|$	$\|V_{pre}\|$	*Test*
MR	2	20	10662	18765	16448	CV
SST-1	5	18	11855	17836	16262	2210
SST-2	2	19	9613	16185	14838	1821
Subj	2	23	10000	21323	17913	CV
TREC	6	10	5952	9592	9125	500
CR	2	19	3775	5340	5046	CV
MPQA	2	3	10606	6246	6083	CV

3. Data and Experimental setup

1. Hyper-parameters and Training

- Activation function : ReLU
- Filter windows (h) : 3, 4, 5 with 100 feature maps each
- Dropout rate (p) : 0.5
- l_2 constraint (s) : 3
- Mini-batch size : 50

- Chosen via a grid search on the SST-2 dev set.

3. Data and Experimental setup

1. Hyper-parameters and Training

- Early Stopping
- 10-fold CV
- SGD over shuffled mini-batches
- Adadelta

3. Data and Experimental setup

2. Pre-trained Word Vectors : word2vec

- Word2vec
- 100 billion words from Google News
- 300 Dimension
- trained using the CBOW architecture

3. Data and Experimental setup

3. Model Variations

- CNN-rand
- CNN-static
- CNN-non-static
- CNN-multichannel

4. Result and Discussion

- Pre-trained vectors are
- 1) good
- 2) ‘universal’ feature extractors
- 3) can be utilized across datasets

Model	MR	SST-1	SST-2	Subj	TREC	CR	MPQA
CNN-rand	76.1	45.0	82.7	89.6	91.2	79.8	83.4
CNN-static	81.0	45.5	86.8	93.0	92.8	84.7	**89.6**
CNN-non-static	**81.5**	48.0	87.2	93.4	93.6	84.3	89.5
CNN-multichannel	81.1	47.4	**88.1**	93.2	92.2	**85.0**	89.4
RAE (Socher et al., 2011)	77.7	43.2	82.4	–	–	–	86.4
MV-RNN (Socher et al., 2012)	79.0	44.4	82.9	–	–	–	–
RNTN (Socher et al., 2013)	–	45.7	85.4	–	–	–	–
DCNN (Kalchbrenner et al., 2014)	–	48.5	86.8	–	93.0	–	–
Paragraph-Vec (Le and Mikolov, 2014)	–	**48.7**	87.8	–	–	–	–
CCAE (Hermann and Blunsom, 2013)	77.8	–	–	–	–	–	87.2
Sent-Parser (Dong et al., 2014)	79.5	–	–	–	–	–	86.3
NBSVM (Wang and Manning, 2012)	79.4	–	–	93.2	–	81.8	86.3
MNB (Wang and Manning, 2012)	79.0	–	–	**93.6**	–	80.0	86.3
G-Dropout (Wang and Manning, 2013)	79.0	–	–	93.4	–	82.1	86.1
F-Dropout (Wang and Manning, 2013)	79.1	–	–	**93.6**	–	81.9	86.3
Tree-CRF (Nakagawa et al., 2010)	77.3	–	–	–	–	81.4	86.1
CRF-PR (Yang and Cardie, 2014)	–	–	–	–	–	82.7	–
SVM_S (Silva et al., 2011)	–	–	–	–	**95.0**	–	–

4. Result and Discussion

1. Multichannel vs Single Channel Models

- What they expected : Prevent Overfitting
- But the results are mixed.
- Further work on regularizing the fine-tuning process is warranted.

4. Result and Discussion

2. Static vs. Non-static Representations

- Fine tuned on the SST2 dataset.

- In Pre-trained word2vec, bad ≈ good
- In Non-static channel, bad ≈ terrible

For the word not in the set

- "!" ≈ effusive expressions
- "," ≈ conjunctive

	Most Similar Words for	
	Static Channel	Non-static Channel
bad	*good* *terrible* *horrible* *lousy*	*terrible* *horrible* *lousy* *stupid*
good	*great* *bad* *terrific* *decent*	*nice* *decent* *solid* *terrific*
n't	*os* *ca* *ireland* *wo*	*not* *never* *nothing* *neither*
!	*2,500* *entire* *jez* *changer*	*2,500* *lush* *beautiful* *terrific*
,	*decasia* *abysmally* *demise* *valiant*	*but* *dragon* *a* *and*

4. Result and Discussion

3. Further Observations

- Achieved more accuracy than existing Max-TDNN model(37.4% -> 45.0%)
- Dropout proved to be such a good regularizer
- When randomly initializing words not in word2vec, we obtained slight improvements by sampling each dimension from U[-a, a] where have the same variance as the pre-trained ones.
- Word2vec trained on google news gave far superior performance than word2vec trained on Wikipedia.
- Adadelta gave similar results to Adagrad but required fewer epochs.

5. Conclusion

- Unsupervised pre-training of word vectors is important ingredient in deep learning for NLP.

6. Reference

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