

Deep Learning  
Do machines know  
the meaning of a word?

Hung-yi Lee

# Language Technology

## spam detection



(<http://spam-filter-review.toptenreviews.com/>)

## Sentiment Analysis

這部電影太糟了

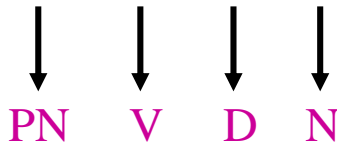
Negative (負雷)

## Retrieval



## Part-of-speech Tagging

John saw the saw.



## Translation

“Machine learning .....”



“機器學習 .....”

## Speech Recognition



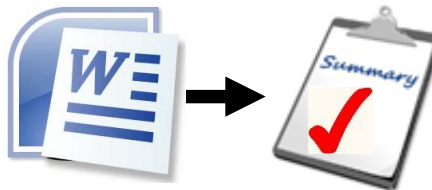
大家好.....

## Name Entity Recognition

這 位 是 李 宏 毅

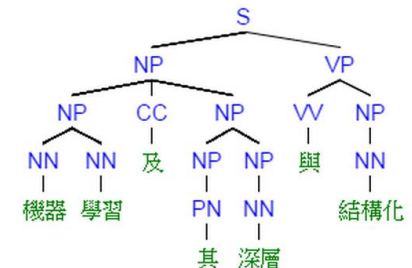
Name of People

## Summarization



document summary

## Syntactic Analysis

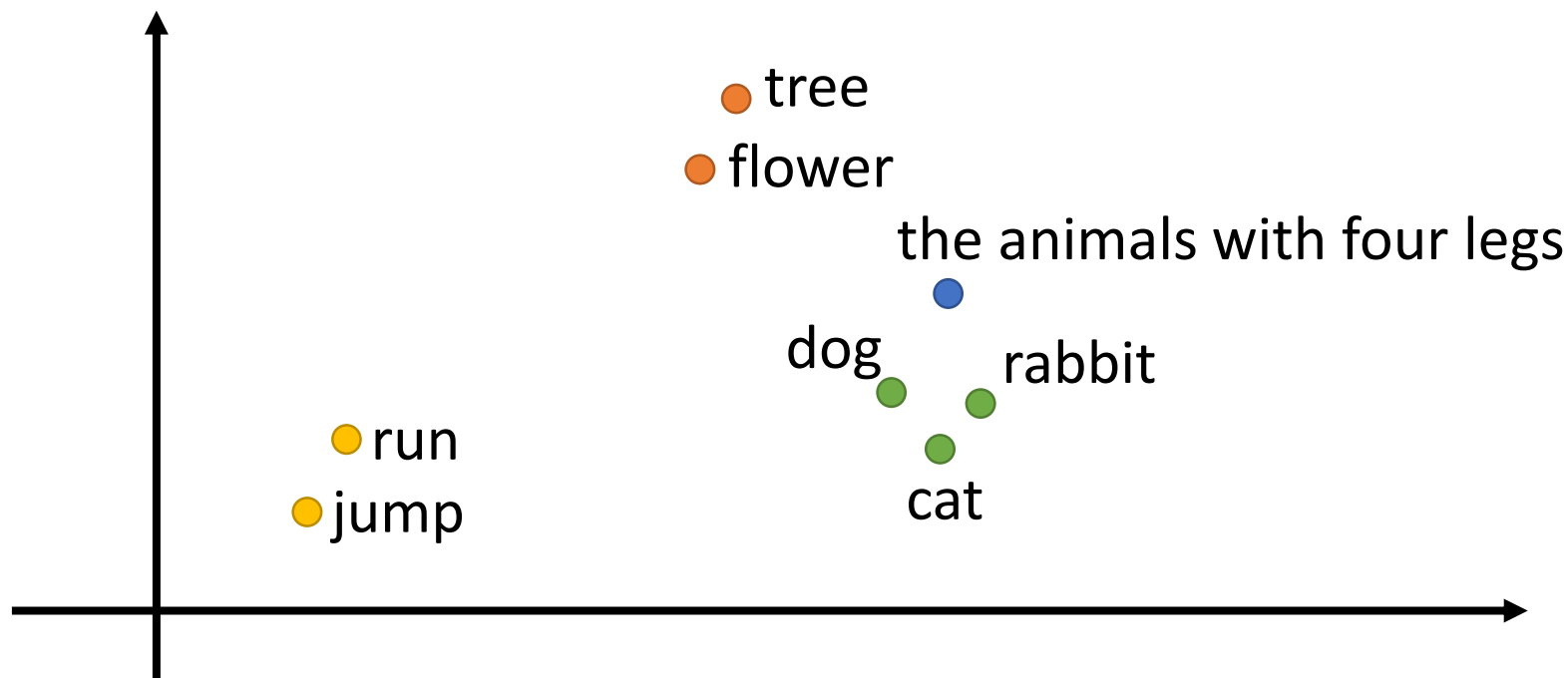


# Do machine really understand human language?



# Meaning Representation

Do machines know the meaning of a word or word sequence?



# Meaning of Word

# Predicting the next word

- Given a sequence of words, predict the next word

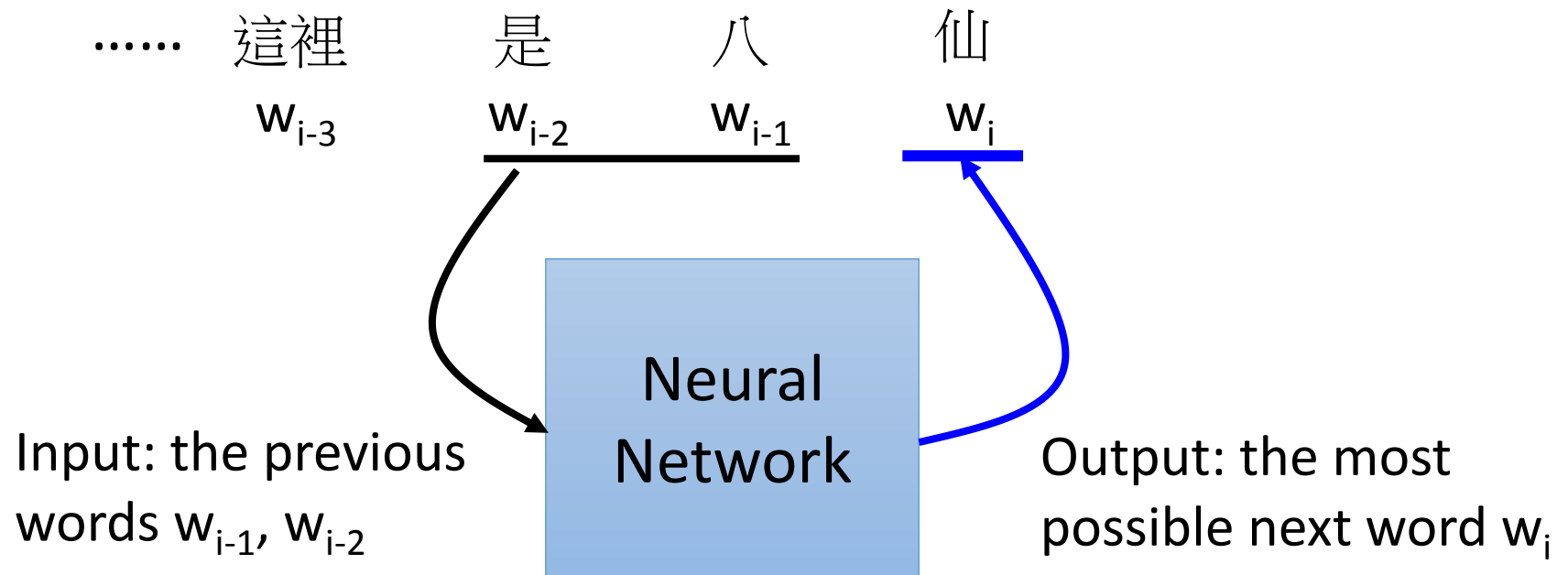
麻煩這系列的請到政黑或其他地方討論好嗎?這裡是人 04/27 00:40

Ref: <http://pttpedia.pixnet.net/blog/post/167961207->

%E9%80%99%E8%A3%A1%E6%98%AF%E5%85%AB%E4%BB%99%E6%A8%82%E5%9C%92

# Predicting the next word

- Given a sequence of words, predict the next word



Each word should be represented as a feature vector.

# Predicting the next word

## 1-of-N Encoding

lexicon = {apple, bag, cat, dog, elephant}

apple = [ 1 0 0 0 0]    The vector is lexicon size.

bag = [ 0 1 0 0 0]    Each dimension corresponds

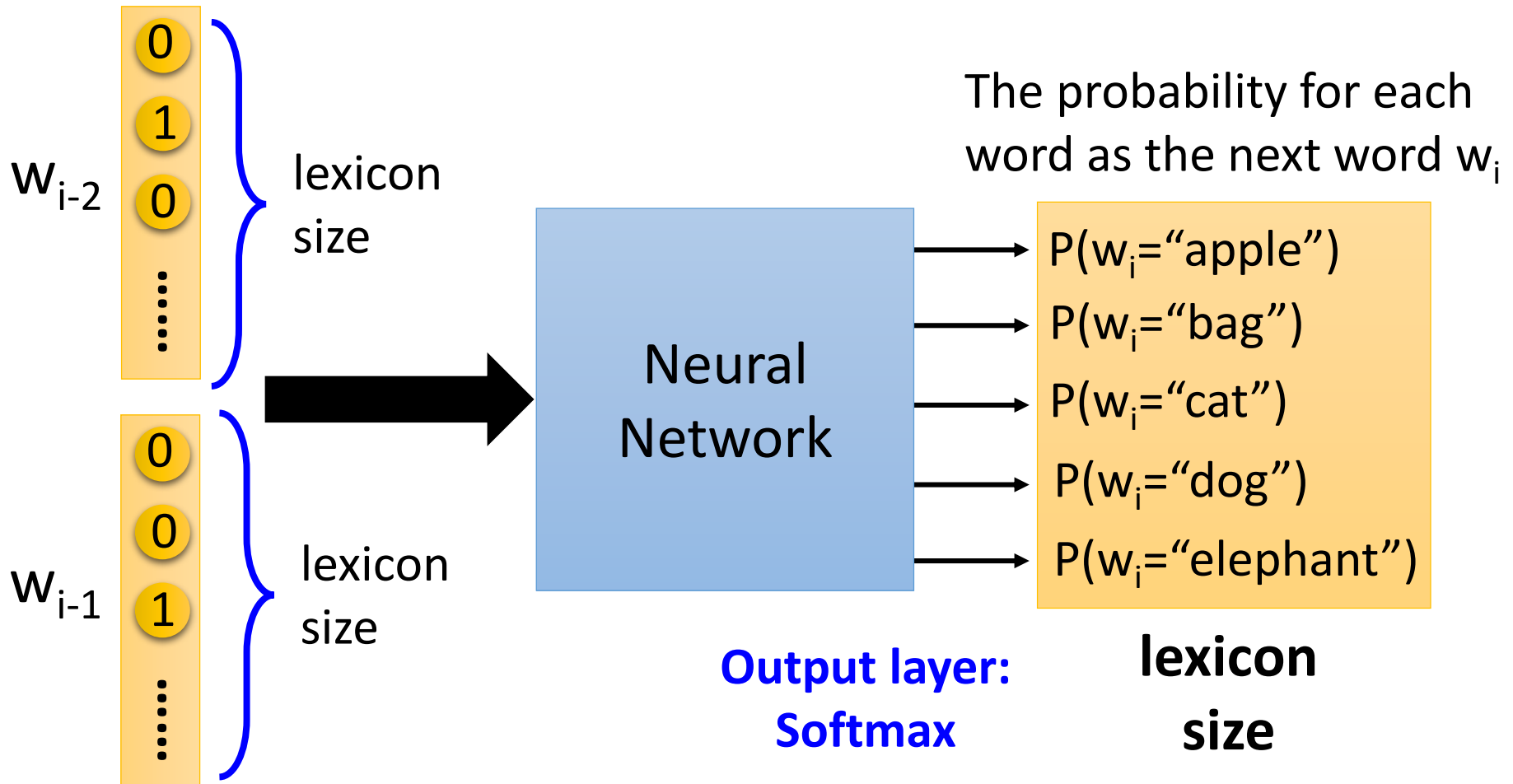
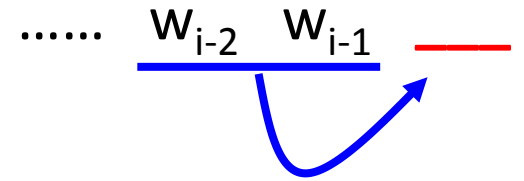
cat = [ 0 0 1 0 0]    to a word in the lexicon

dog = [ 0 0 0 1 0]    The dimension for the word

elephant = [ 0 0 0 0 1]    is 1, and others are 0



# Predicting the next word



# Predicting the next word

Application?

- Training:

Collect data:

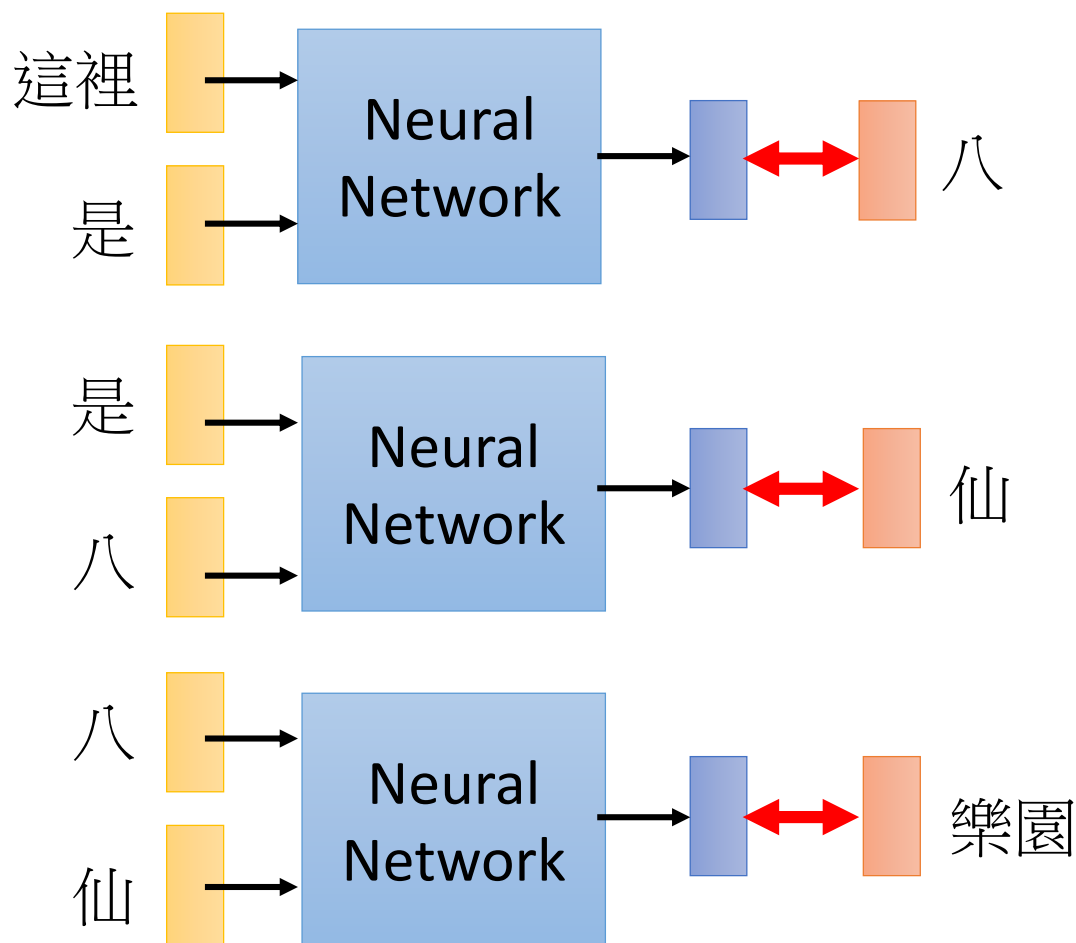
這裡 是 八仙 樂園

.....

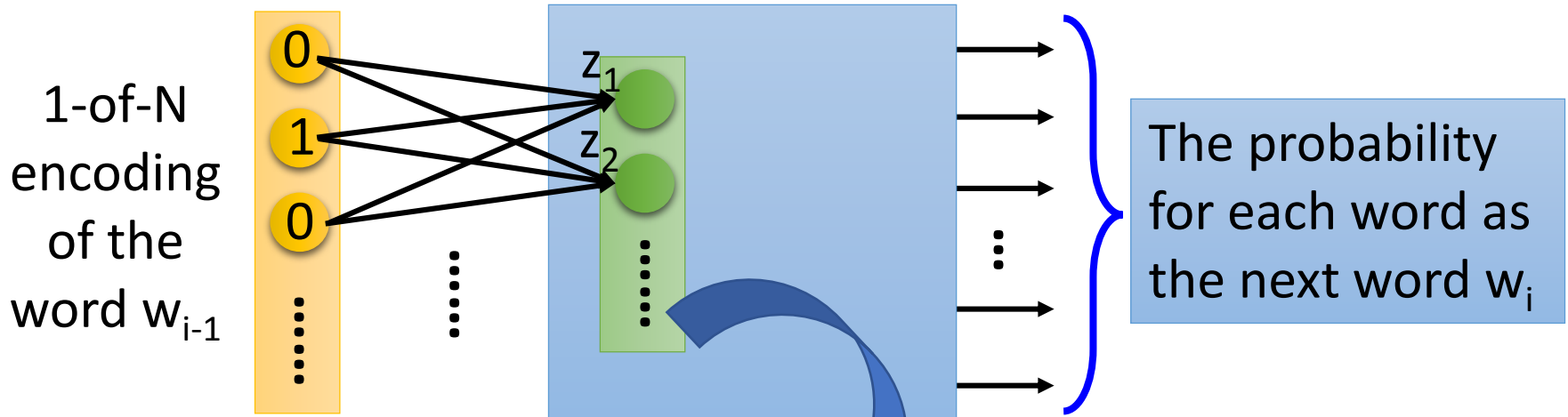
.....

.....

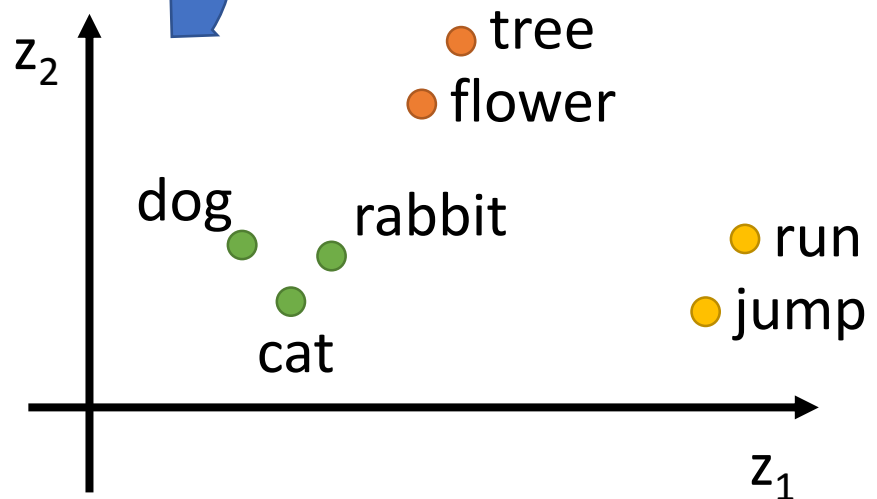
**Minimizing  
cross entropy**



# Word Vector

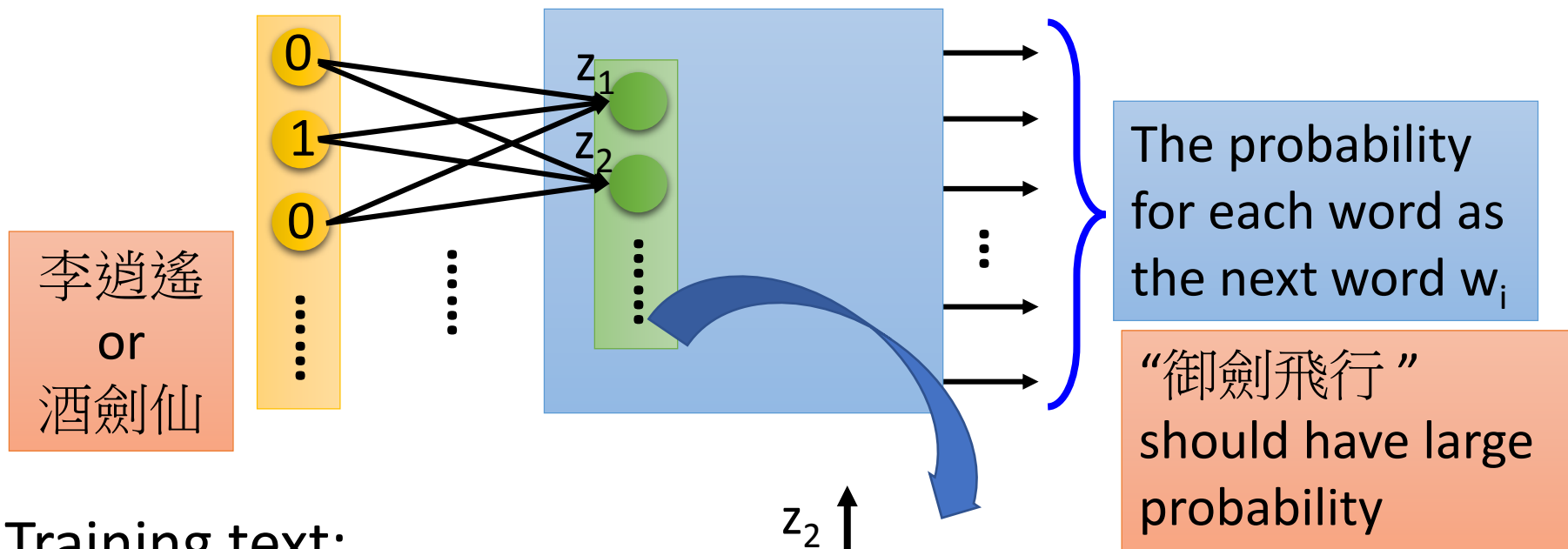


- Take out the input of the neurons in the first layer
- Use it to represent a word  $w$
- Word vector, word embedding feature:  $V(w)$



# Word Vector

You shall know a word  
by the company it keeps



Training text:

..... 李逍遙 御劍飛行 .....

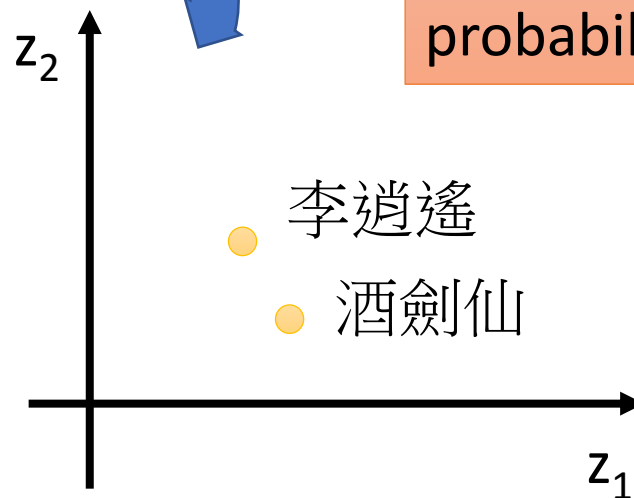
$w_{i-1}$

$w_i$

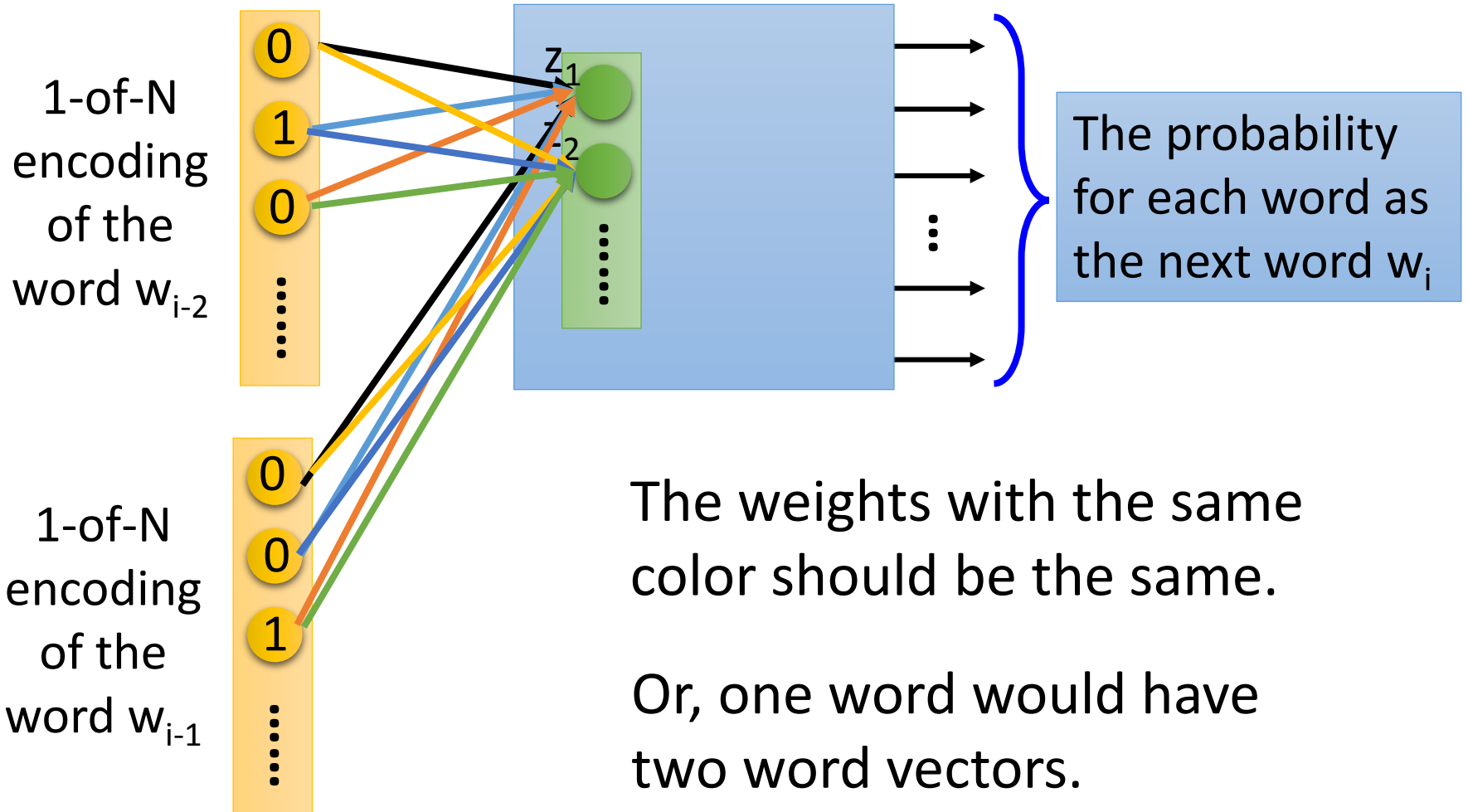
..... 酒劍仙 御劍飛行 .....

$w_{i-1}$

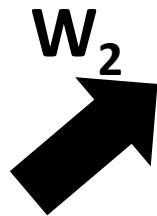
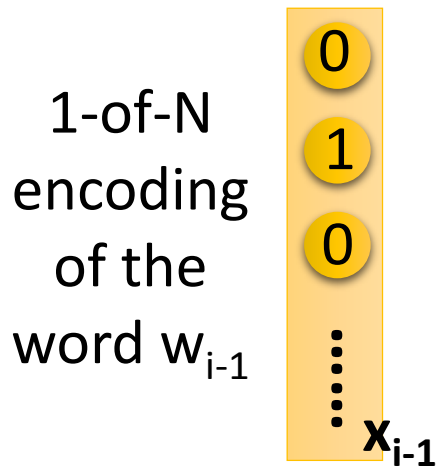
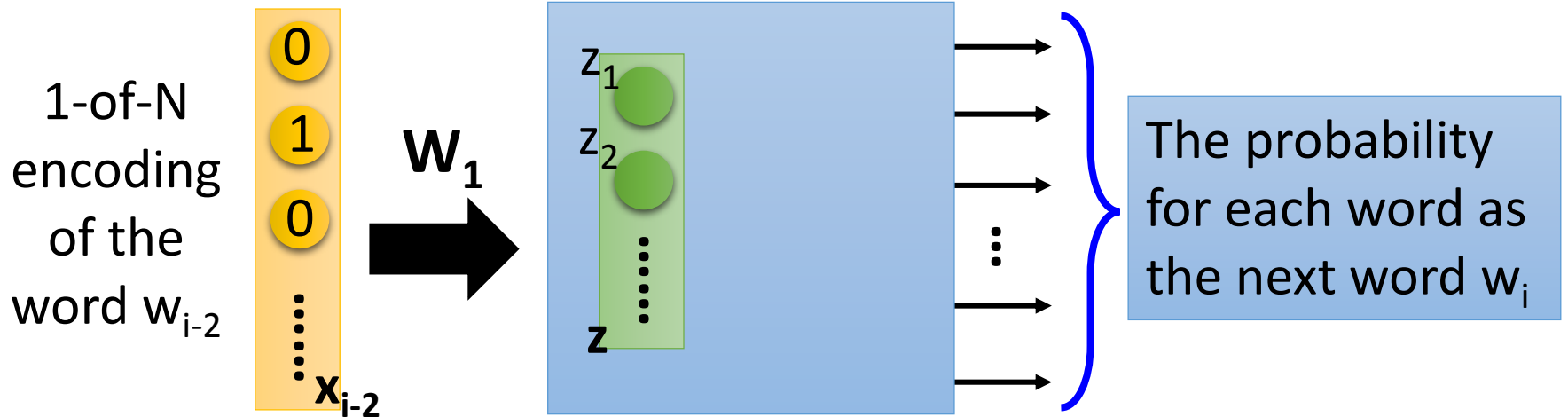
$w_i$



# Word Vector – Sharing Parameters



# Word Vector – Sharing Parameters



The length of  $\mathbf{x}_{i-1}$  and  $\mathbf{x}_{i-2}$  are both  $|V|$ .

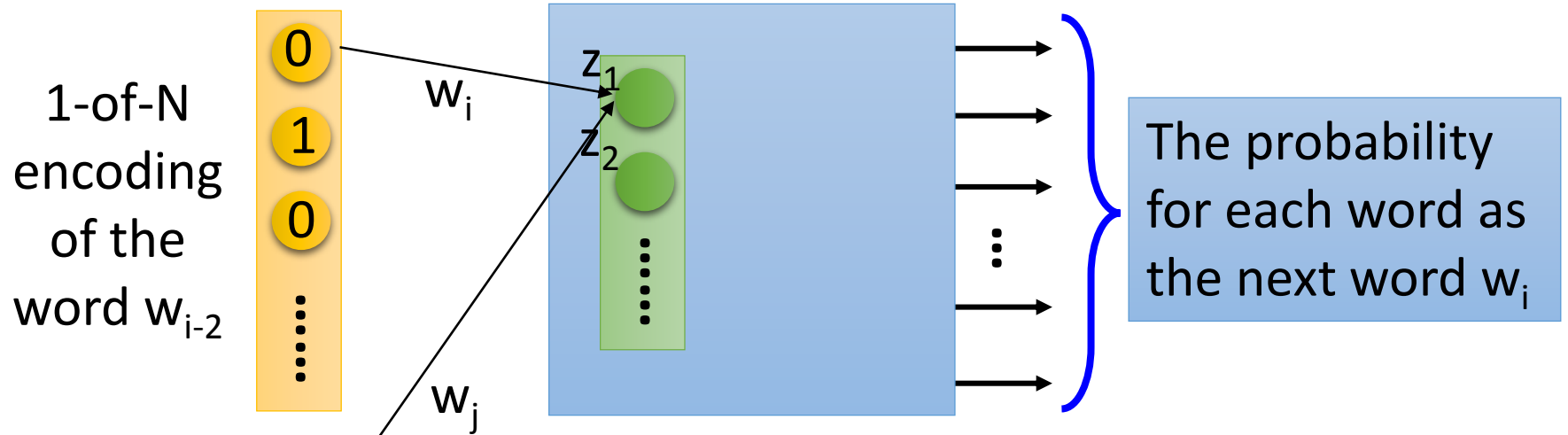
The length of  $\mathbf{z}$  is  $|Z|$ .

$$\mathbf{z} = \mathbf{W}_1 \mathbf{x}_{i-2} + \mathbf{W}_2 \mathbf{x}_{i-1}$$

The weight matrix  $\mathbf{W}_1$  and  $\mathbf{W}_2$  are both  $|Z| \times |V|$  matrices.

$$\mathbf{W}_1 = \mathbf{W}_2 = \mathbf{W} \Rightarrow \mathbf{z} = \mathbf{W} (\mathbf{x}_{i-2} + \mathbf{x}_{i-1})$$

# Word Vector – Sharing Parameters



How to make  $w_i$  equal to  $w_j$

Given  $w_i$  and  $w_j$  the same initialization

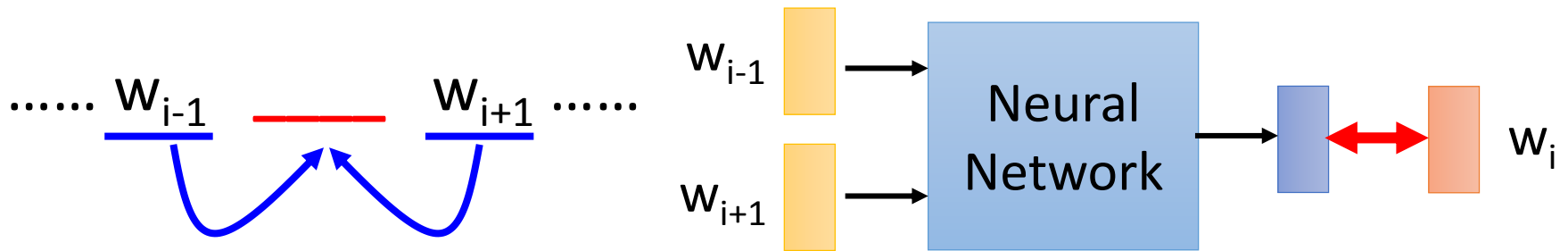
$$w_i \leftarrow w_i - \eta \frac{\partial C}{\partial w_i} - \eta \frac{\partial C}{\partial w_j}$$

$$w_j \leftarrow w_j - \eta \frac{\partial C}{\partial w_j} - \eta \frac{\partial C}{\partial w_i}$$

# Word Vector

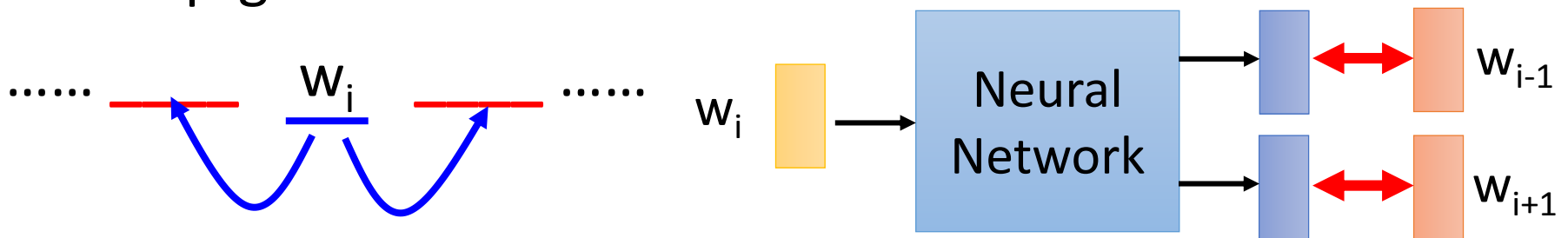
## – Various Architectures

- Continuous bag of word (CBOW) model



*predicting the word given its context*

- Skip-gram

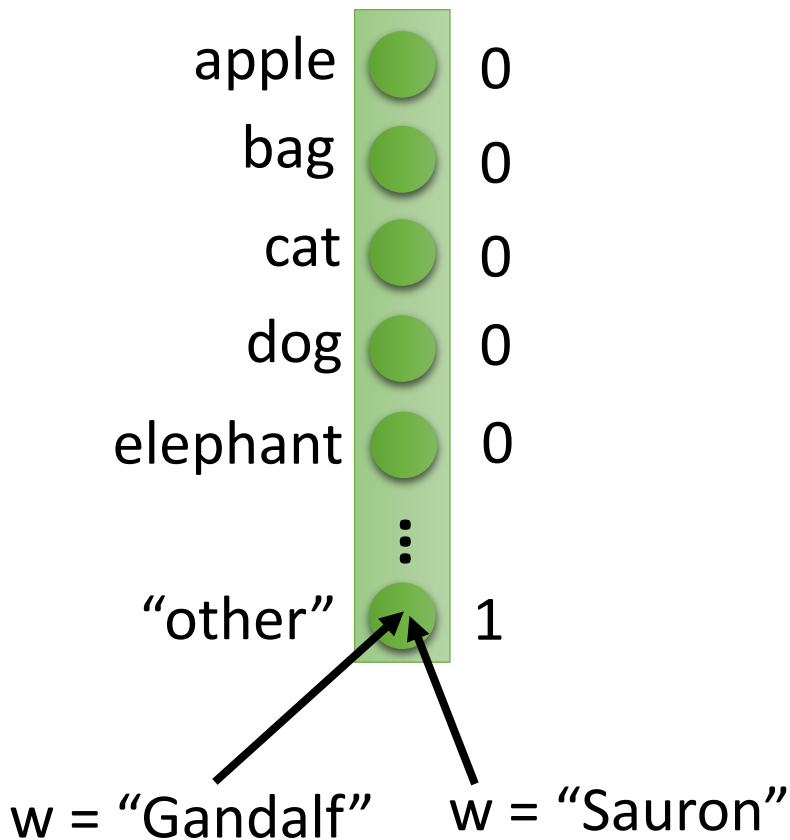


*predicting the context given a word*

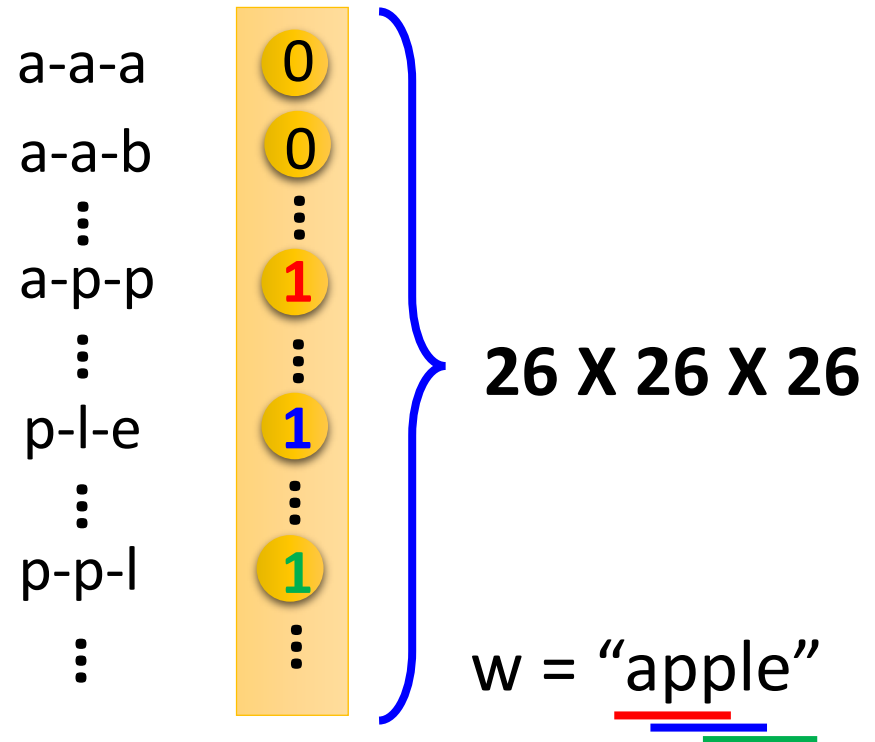


# Beyond 1-of-N encoding

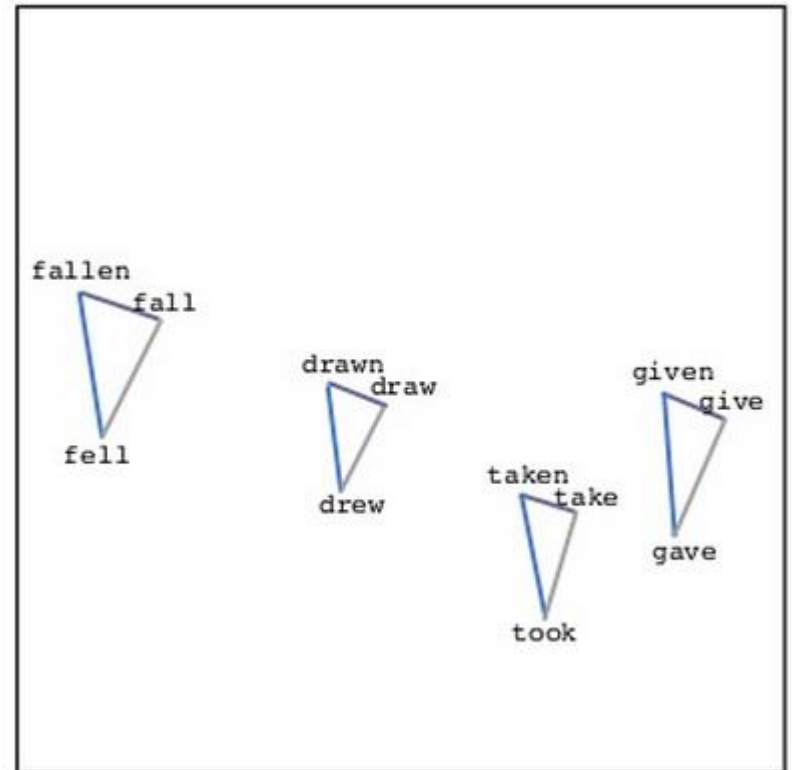
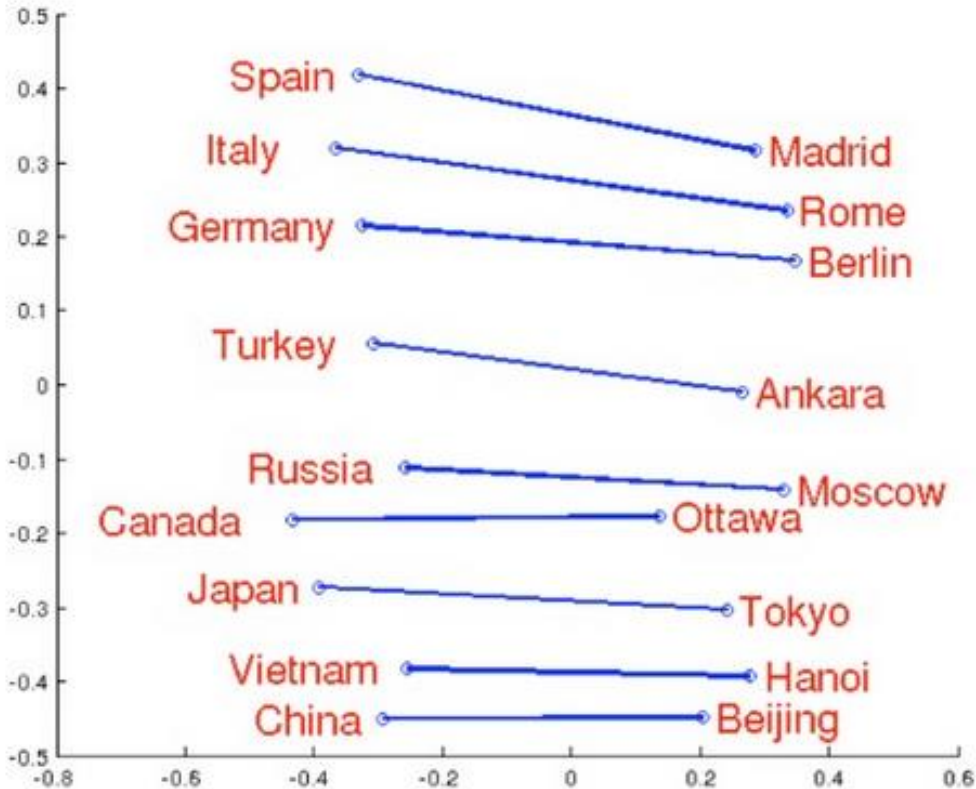
## Dimension for "Other"



## Word hashing



# Word Vector



Source: <http://www.slideshare.net/hustwj/cikm-keynotenov2014>

Word Vector  $\approx V(\text{Germany}) - V(\text{Rome}) + V(\text{Italy})$

- Characteristics

$$V(\text{hotter}) - V(\text{hot}) \approx V(\text{bigger}) - V(\text{big})$$

$$V(\text{Rome}) - V(\text{Italy}) \approx V(\text{Berlin}) - V(\text{Germany})$$

$$V(\text{king}) - V(\text{queen}) \approx V(\text{uncle}) - V(\text{aunt})$$

- Solving analogies

Rome : Italy = Berlin : ?

Compute  $V(\text{Berlin}) - V(\text{Rome}) + V(\text{Italy})$

Find the word  $w$  with the closest  $V(w)$

# Demo

- Model used in demo is provided by 陳仰德
  - Part of the project done by 陳仰德、林資偉
  - TA: 劉元銘
  - Training data is from PTT (collected by 葉青峰)

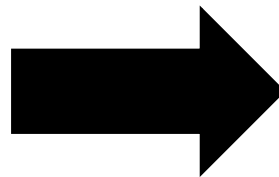
# Meaning of Word Sequence

# Meaning of Word Sequence

- word sequences with different lengths → the vector with the same length
  - The vector representing the meaning of the word sequence
  - A word sequence can be a document or a paragraph



word sequence  
(a document or paragraph)



# Meaning of Word Sequence

## - Outline

Deep Structured  
Semantic Model  
(DSSM)

- Application: Information Retrieval (IR)

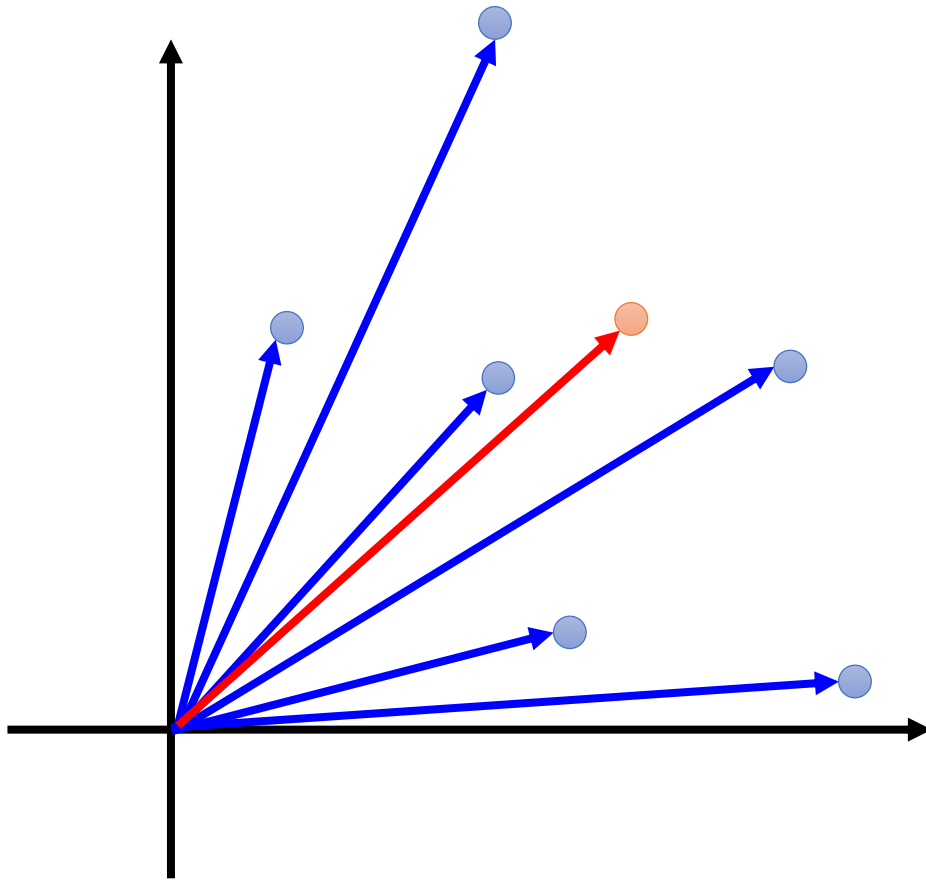
Recursive Deep  
Model

- Application: Sentiment Analysis

Paragraph Vector

- Unsupervised

# Information Retrieval (IR)



## *Vector Space Model*

The documents are vectors in the space.

The query is also a vector.

How to use a vector to represent word sequences



# Information Retrieval (IR)

## Bag-of-words

word string s1:  
"This is an apple"

|       |   |   |
|-------|---|---|
| this  | ● | 1 |
| is    | ● | 1 |
| a     | ● | 0 |
| an    | ● | 1 |
| apple | ● | 1 |
| pen   | ● | 0 |
|       | ⋮ |   |

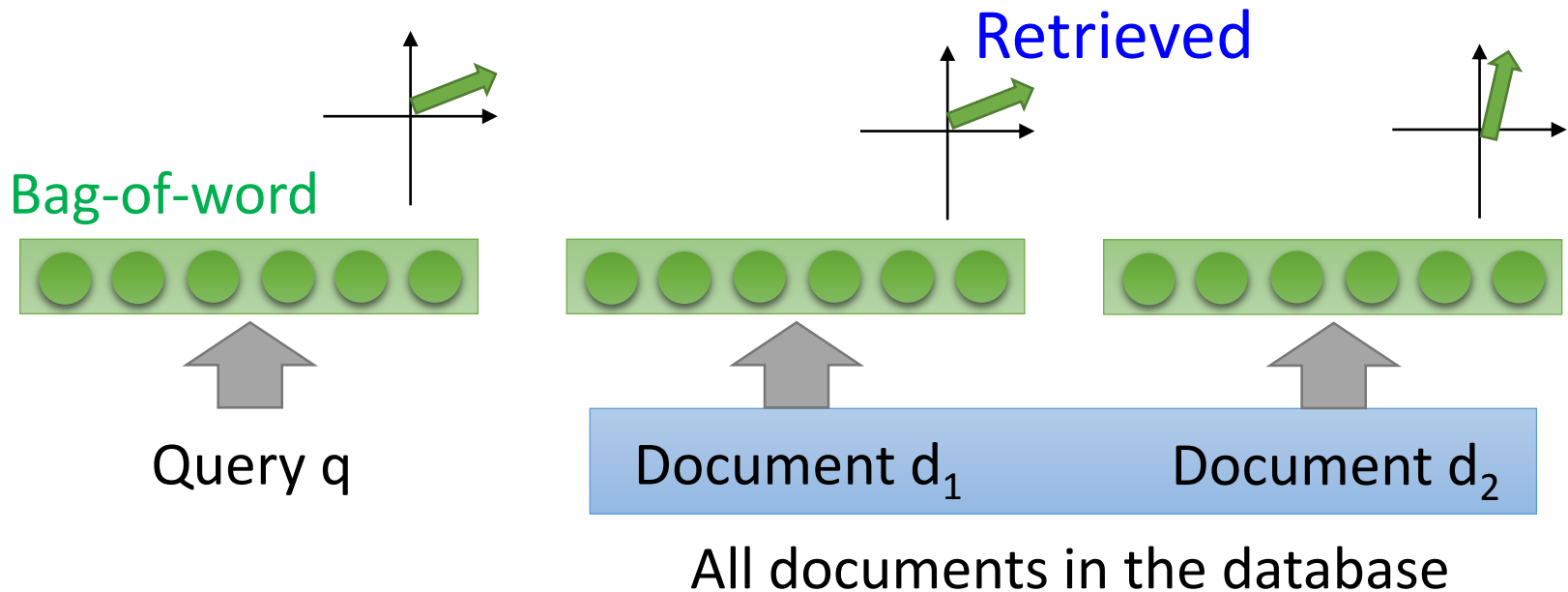
word string s2:  
"This is a pen"

|       |   |   |
|-------|---|---|
| this  | ● | 1 |
| is    | ● | 1 |
| a     | ● | 1 |
| an    | ● | 0 |
| apple | ● | 0 |
| pen   | ● | 1 |
|       | ⋮ |   |

Weighted by IDF

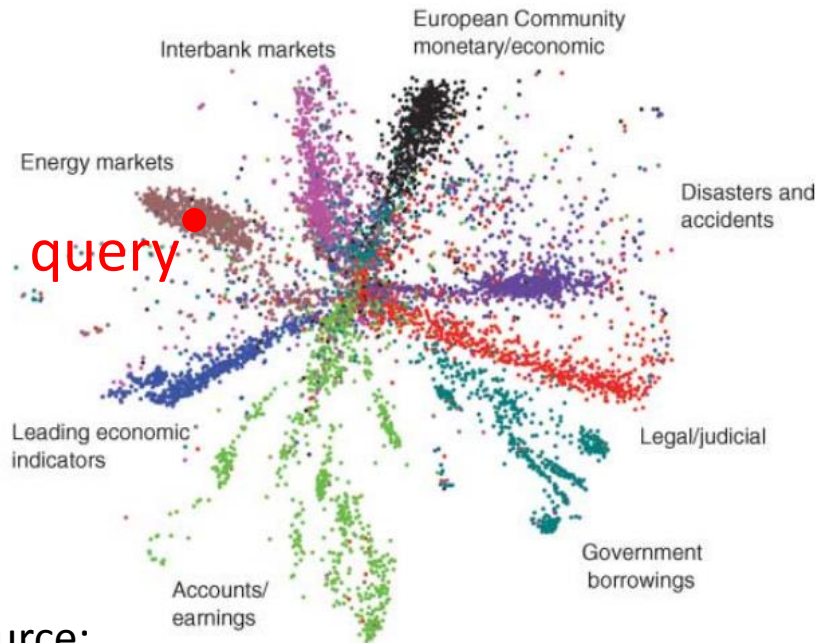
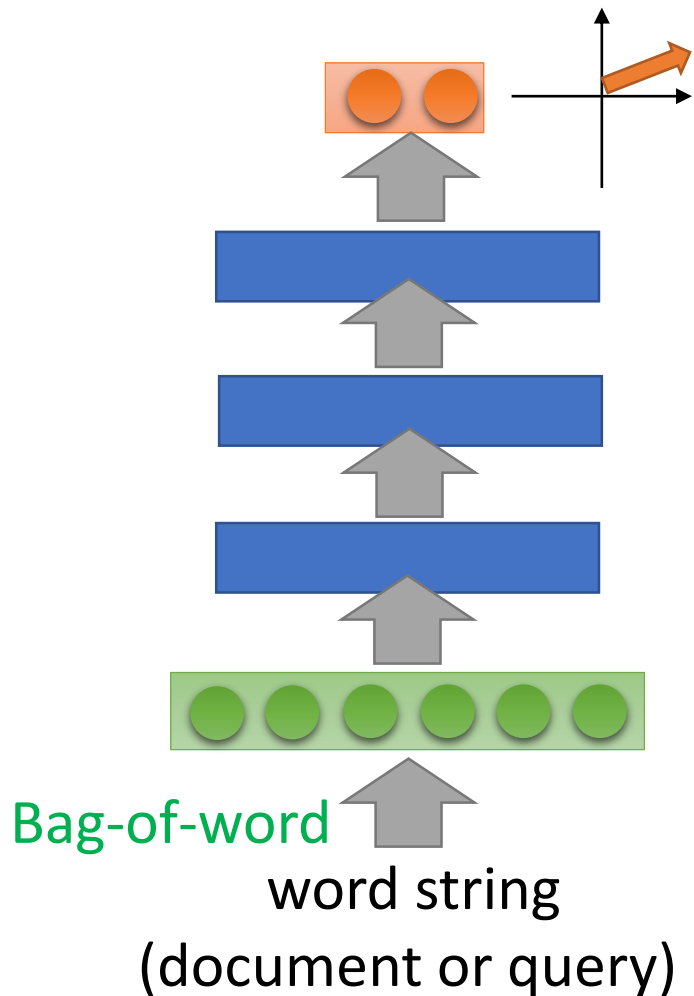
# Information Retrieval (IR)

## Vector Space Model + Bag-of-words



- All the words are treated as discrete tokens
- Never consider different words can have the same meaning, and the same word can have different meanings

# IR - Semantic Embedding



Source:

<http://www.cs.toronto.edu/~hinton/science.pdf>

How to achieve that? (No target .....)

Auto-encoder is one solution,  
but not today

# DSSM

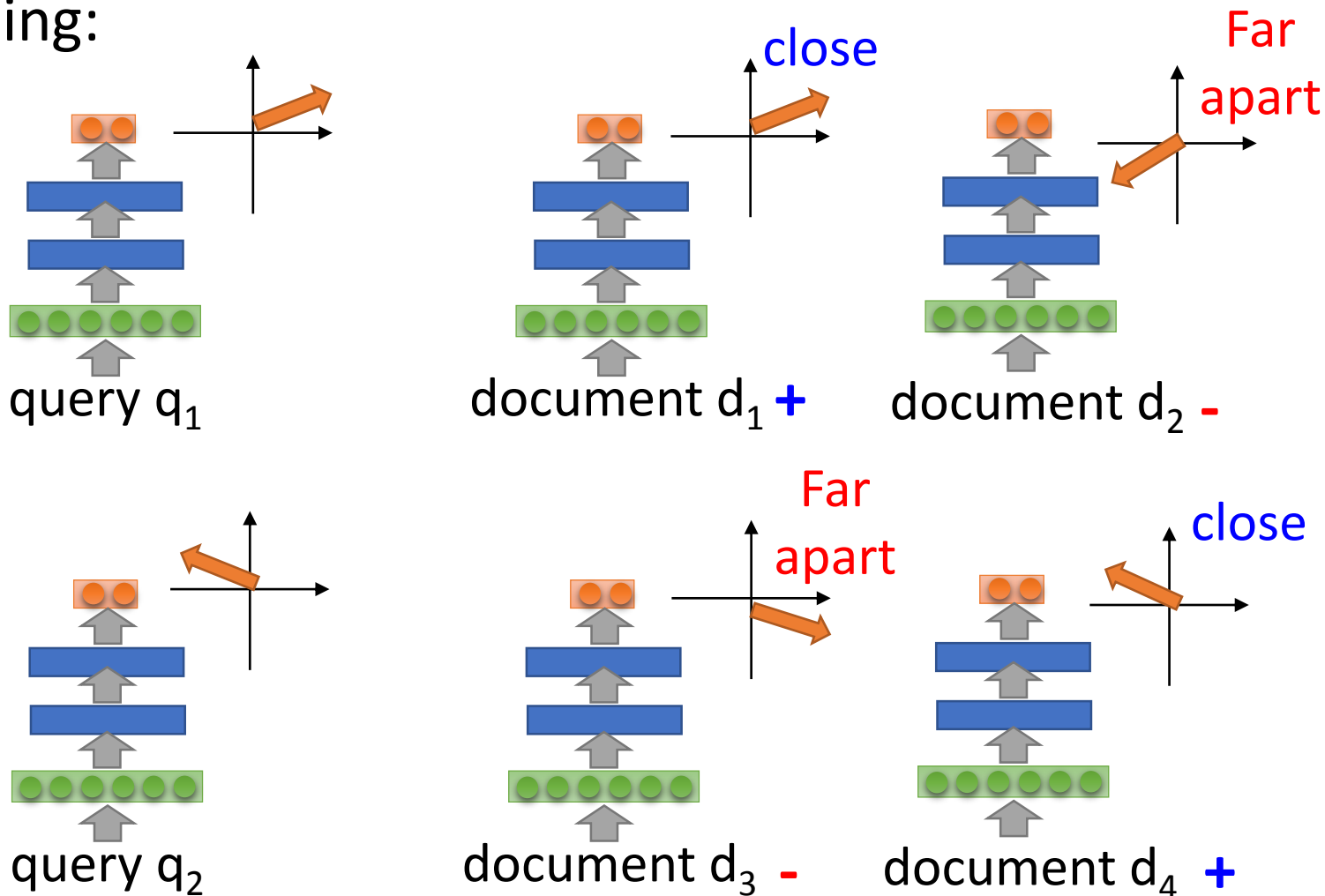
Click-through data:  $q_1 \rightarrow d_1 : + \quad d_2 : -$



$q_2 \rightarrow d_3 : - \quad d_4 : +$

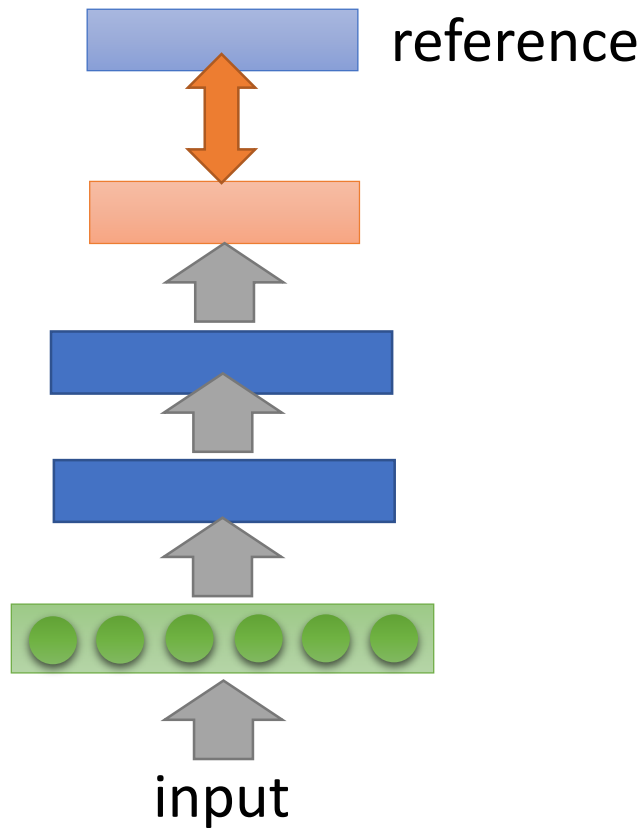
.....

Training:

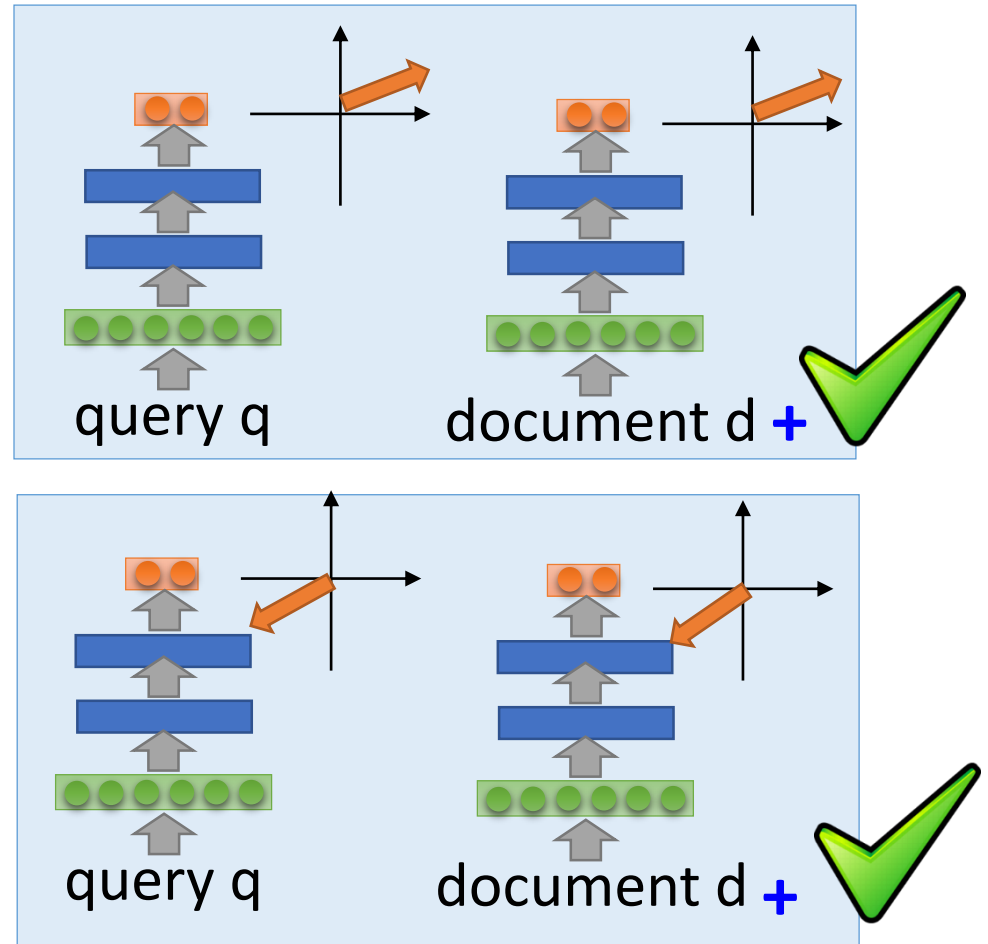


# DSSM v.s. Typical DNN

## Typical DNN



## DSSM

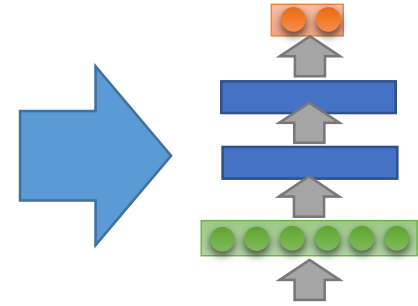


Click-through data:  $q_1 \rightarrow d_1 : + \quad d_2 : -$

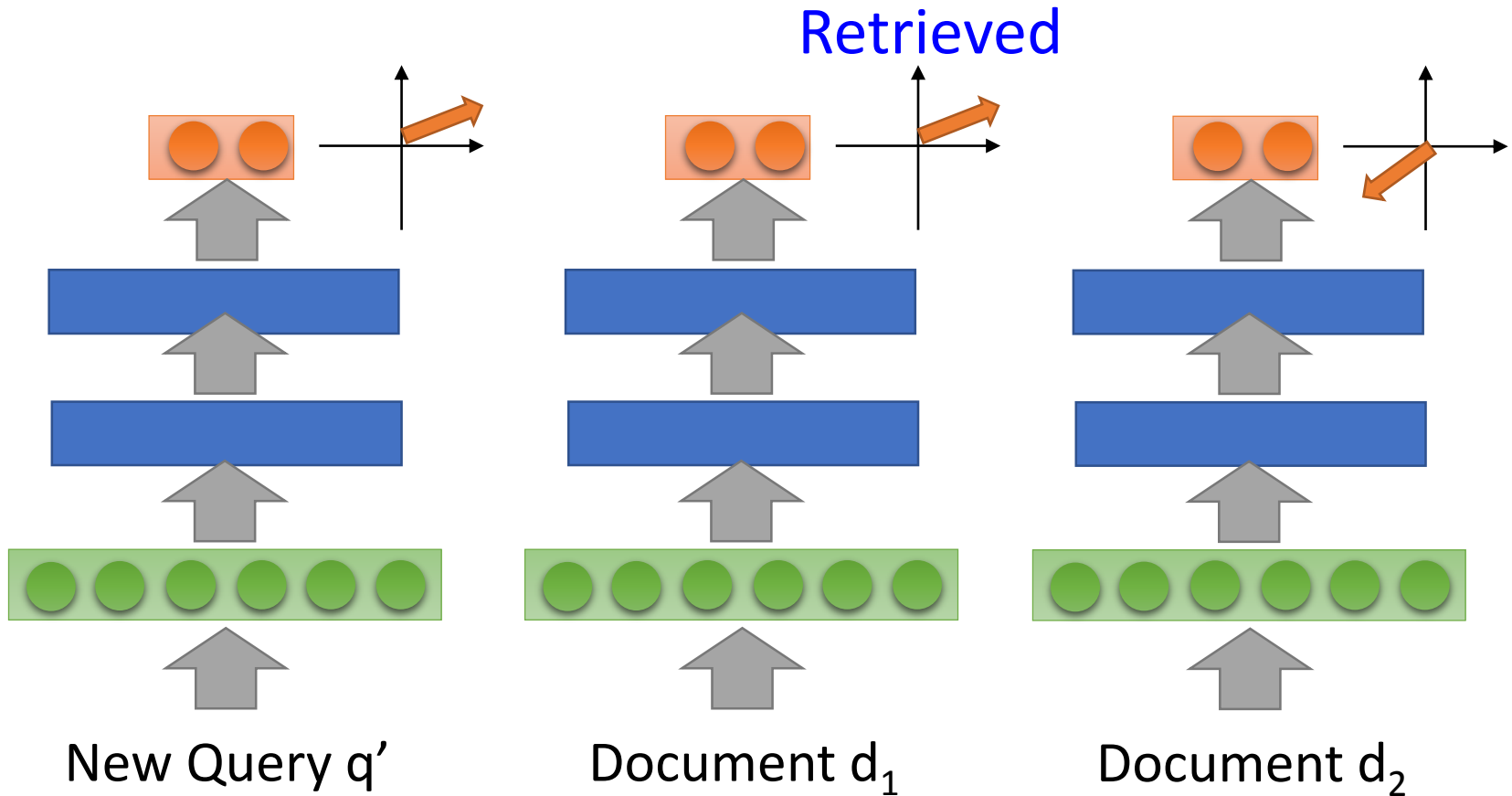


$q_2 \rightarrow d_3 : - \quad d_4 : +$

.....

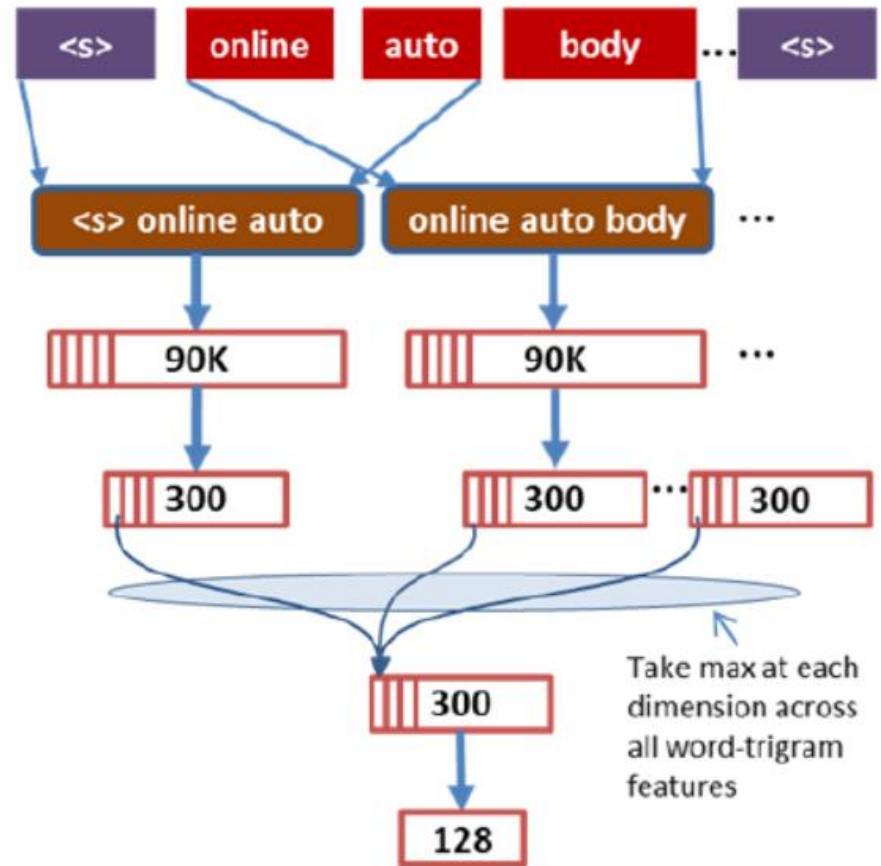


- How to do retrieval?



# More ...

- **Convolutional DSSM:**  
<http://www.iro.umontreal.ca/~lisa/pointeurs/ir0895-he-2.pdf>



# Meaning of Word Sequence

## - Outline

Deep Structured  
Semantic Model  
(DSSM)

- Application: Information Retrieval (IR)

Recursive Deep  
Model

- Application: Sentiment Analysis

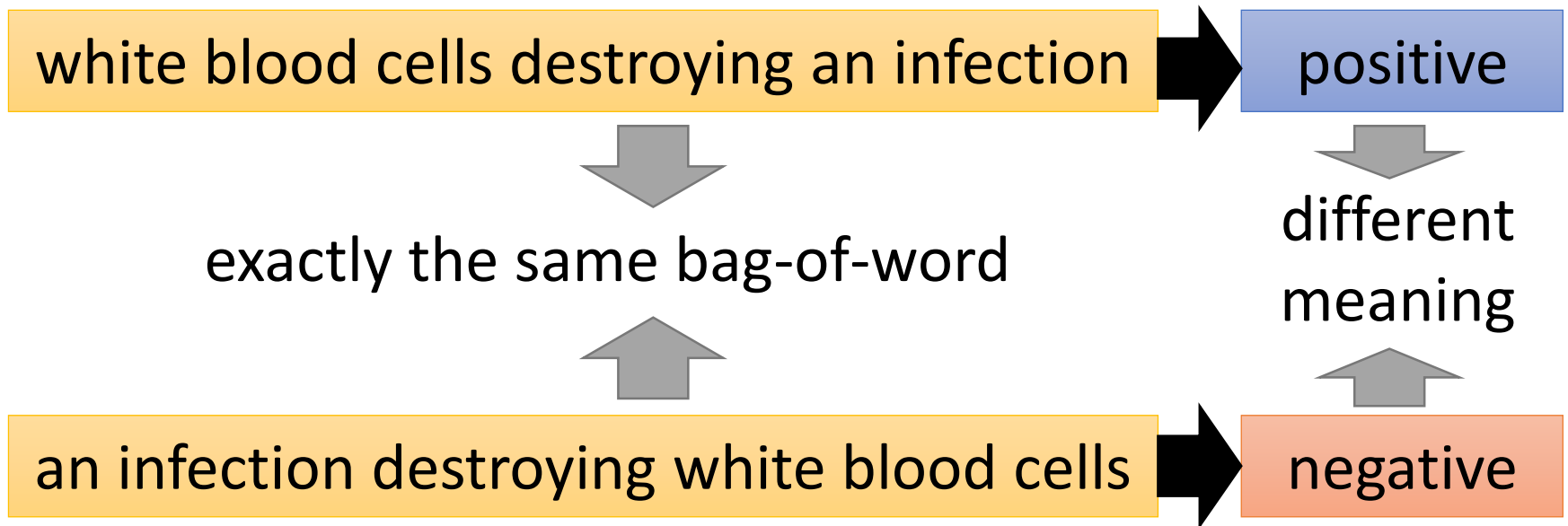
Paragraph Vector

- Unsupervised



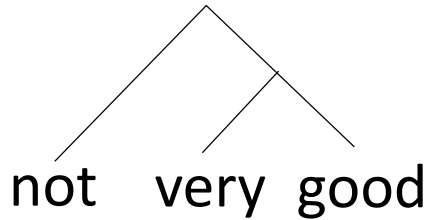
# Recursive Deep Model

- When understanding the meaning of a word sequence, the order of the words can not be ignore.



# Recursive Deep Model

syntactic structure



How to do it is out of the scope

word sequence:

not

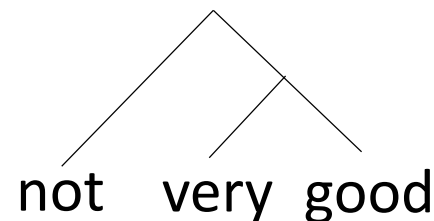
very

good

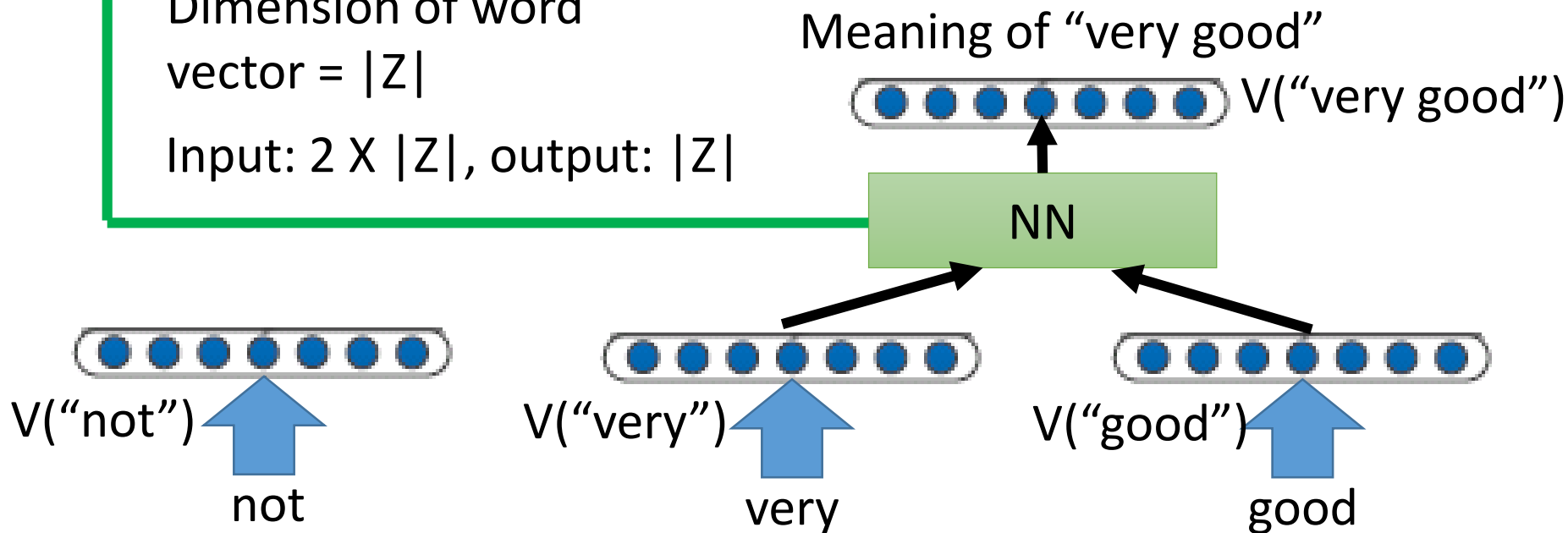
# Recursive Deep Model

By composing the two meaning, what should the meaning be.

syntactic structure



Dimension of word vector =  $|Z|$   
Input:  $2 \times |Z|$ , output:  $|Z|$



# Recursive Deep Model

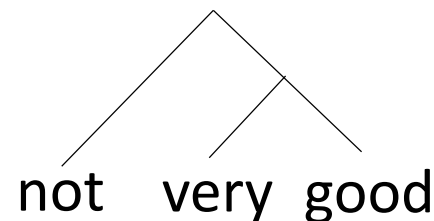
$$V(w_A w_B) \neq V(w_A) + V(w_B)$$

“not”: neutral

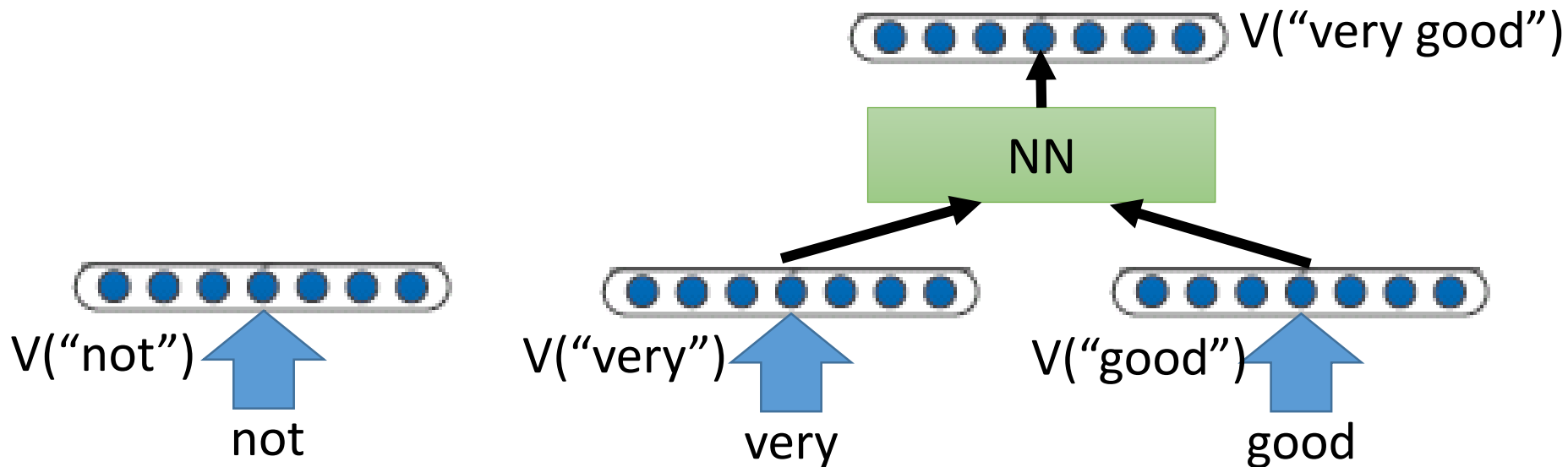
“good”: positive

“not good”: negative

syntactic structure



Meaning of “very good”



# Recursive Deep Model

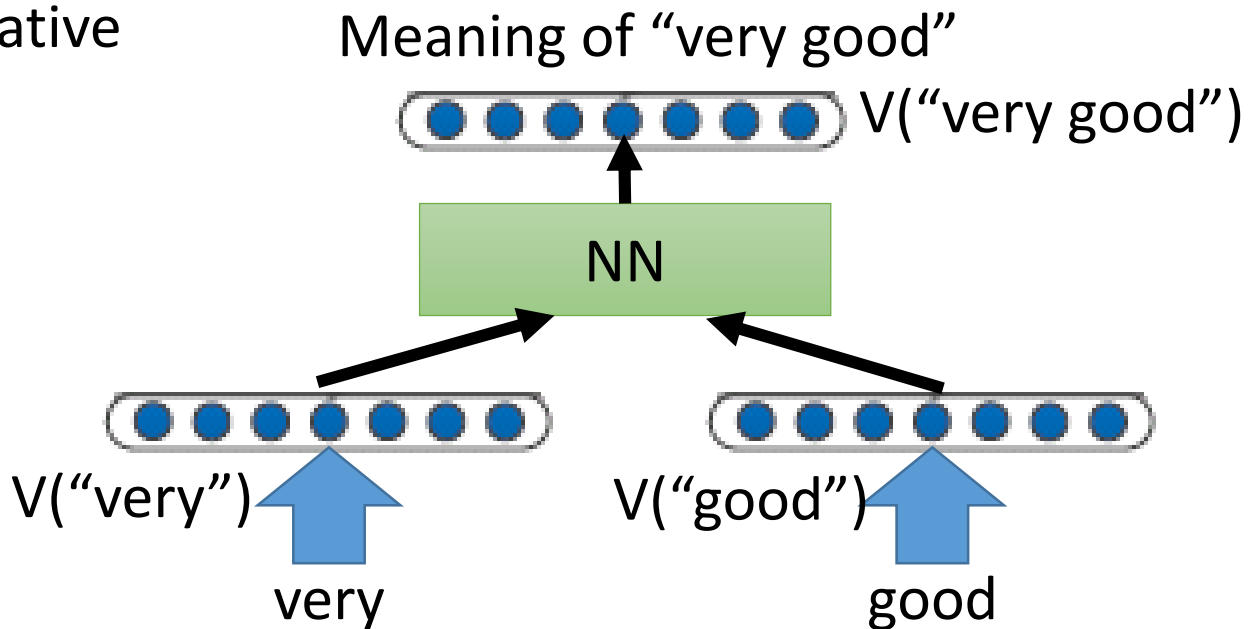
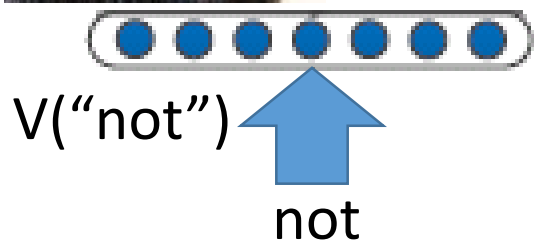
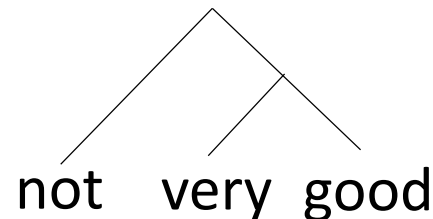
$$V(w_A w_B) \neq V(w_A) + V(w_B)$$

“棒”: positive

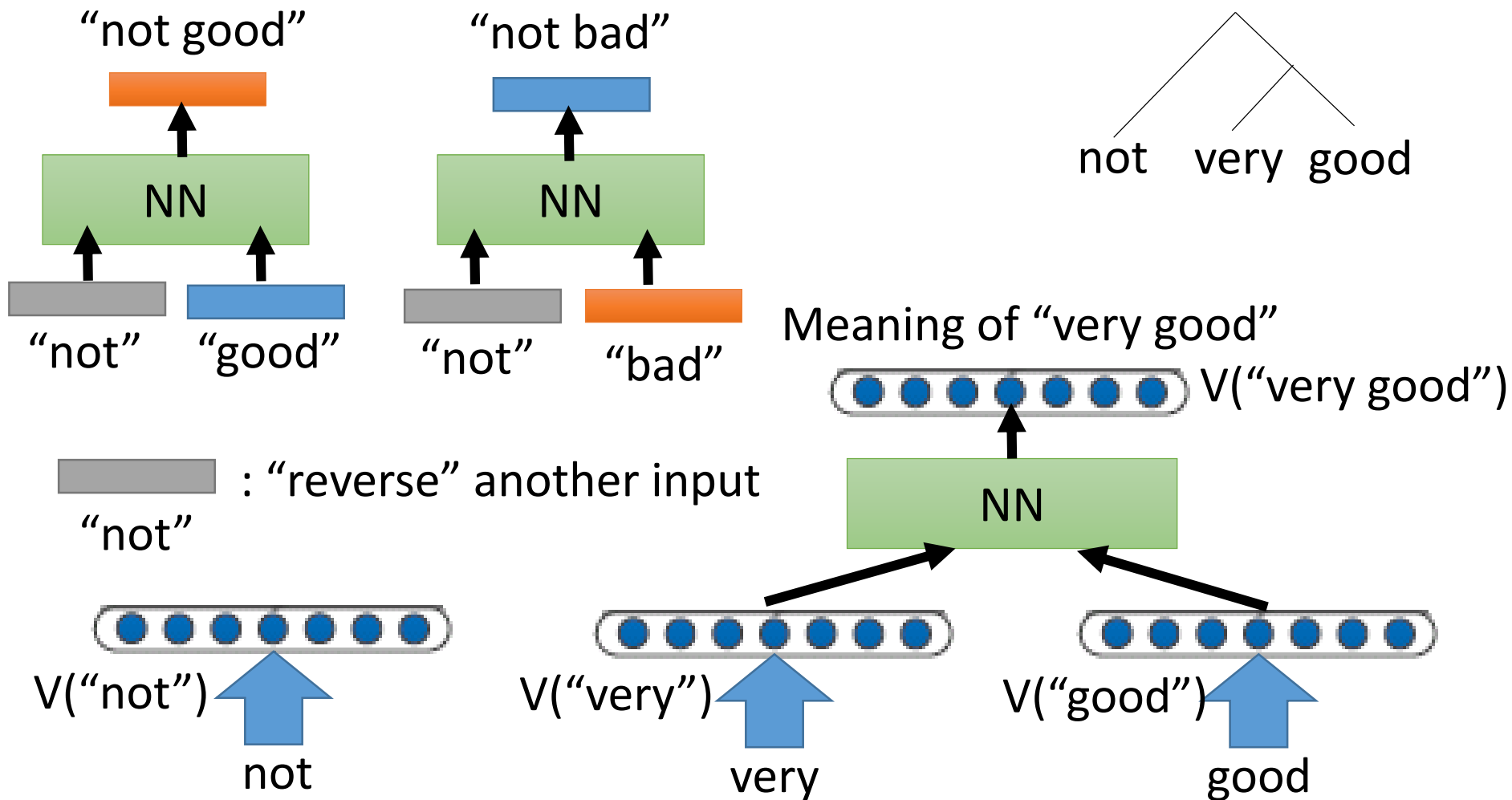
“好棒”: positive

“好棒棒”: negative

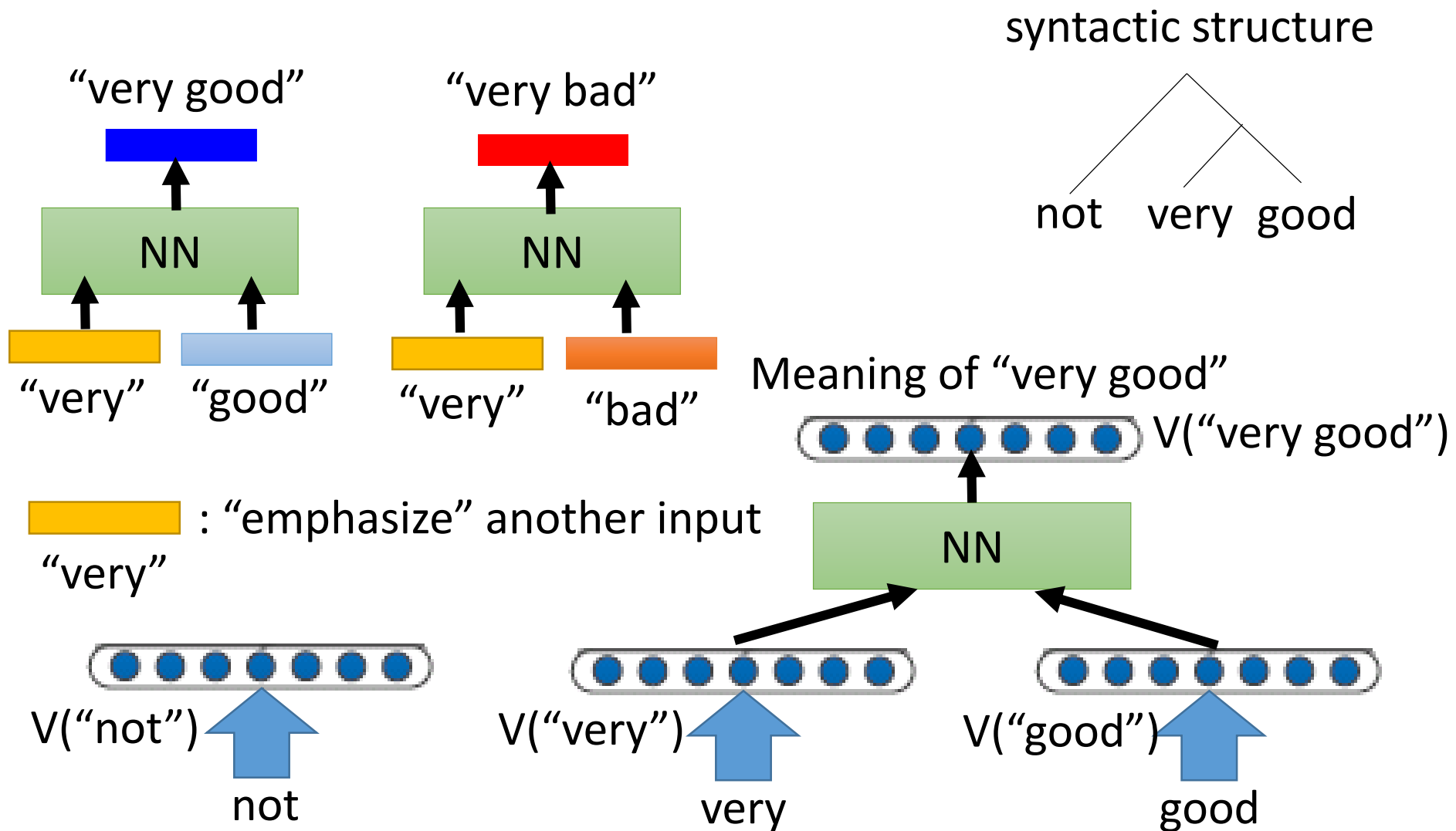
syntactic structure



# Recursive Deep Model



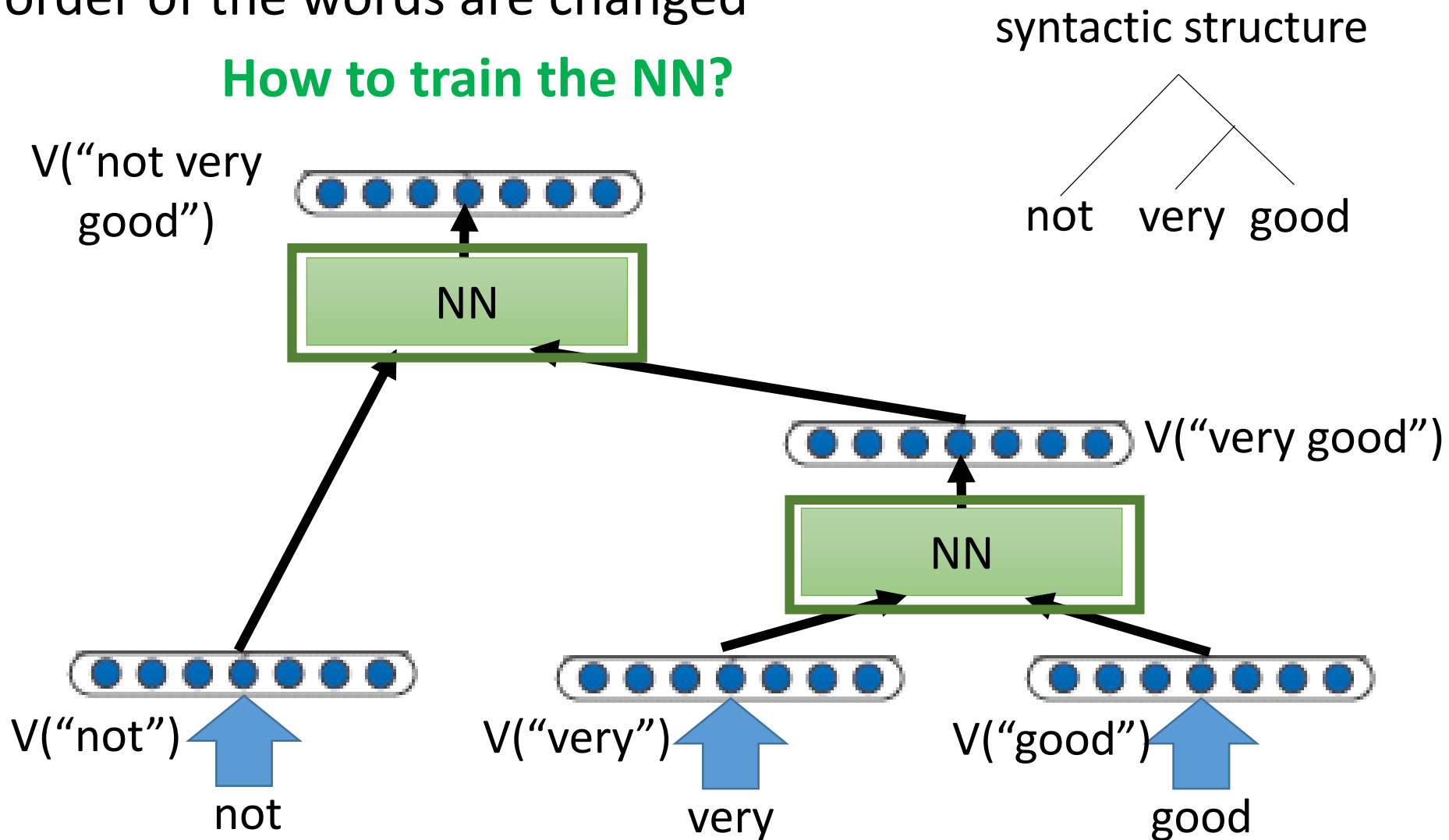
# Recursive Deep Model



The word order is considered.

The representation of the sequence will change if the order of the words are changed

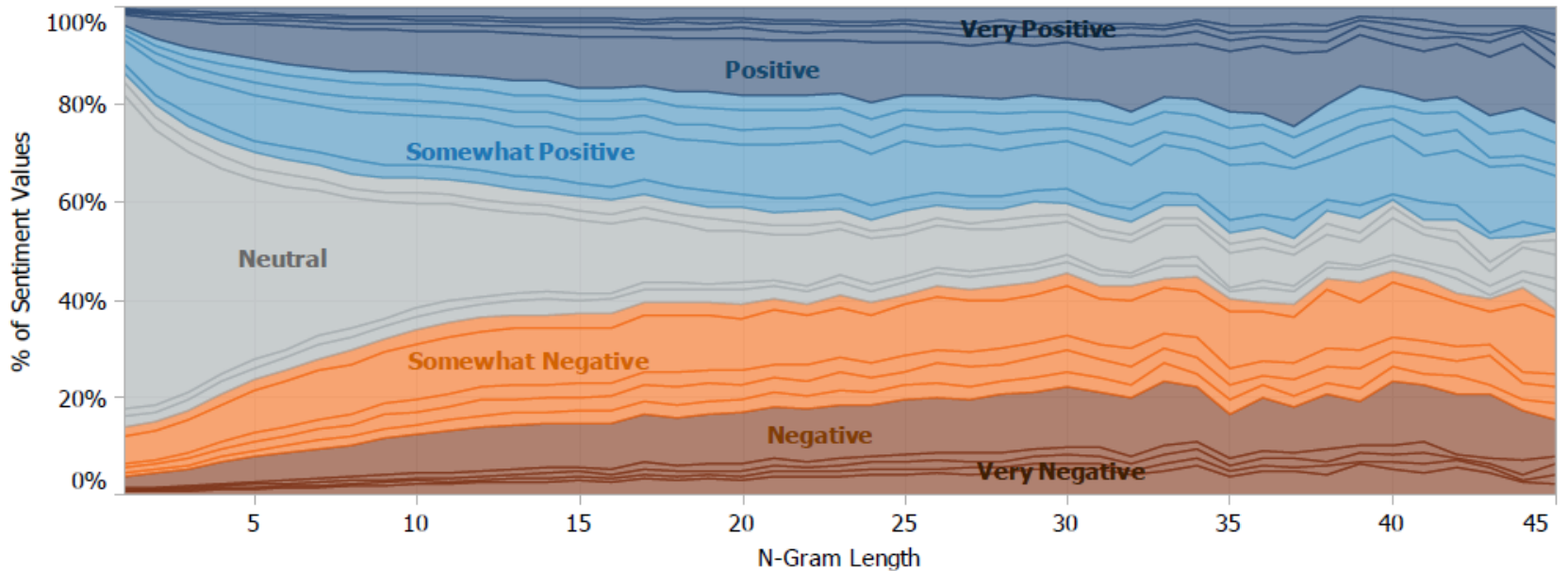
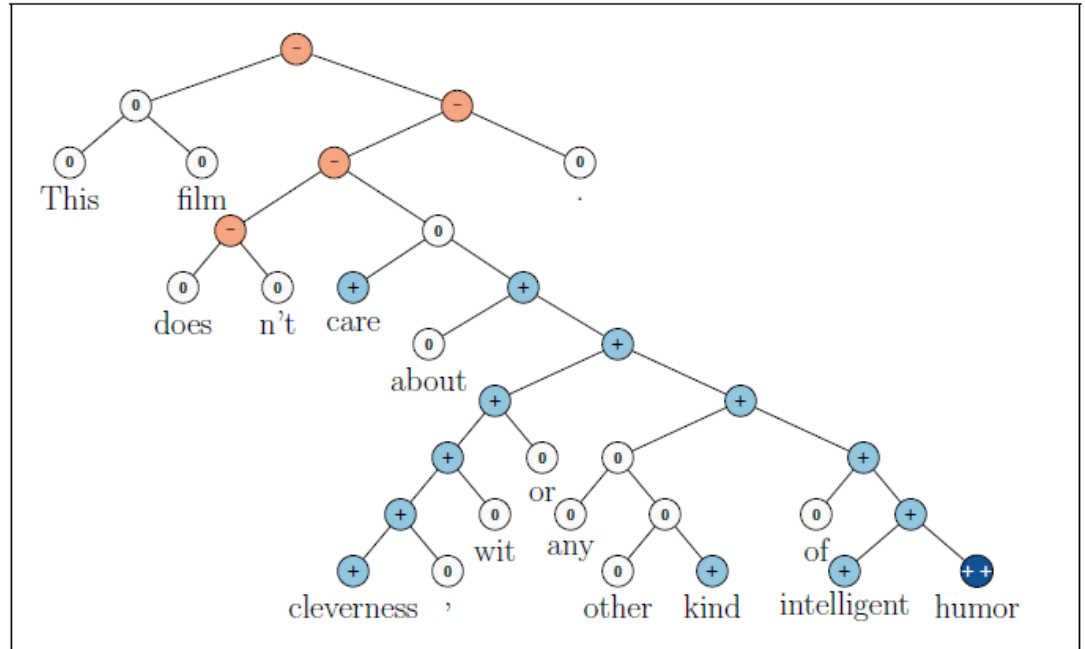
## How to train the NN?

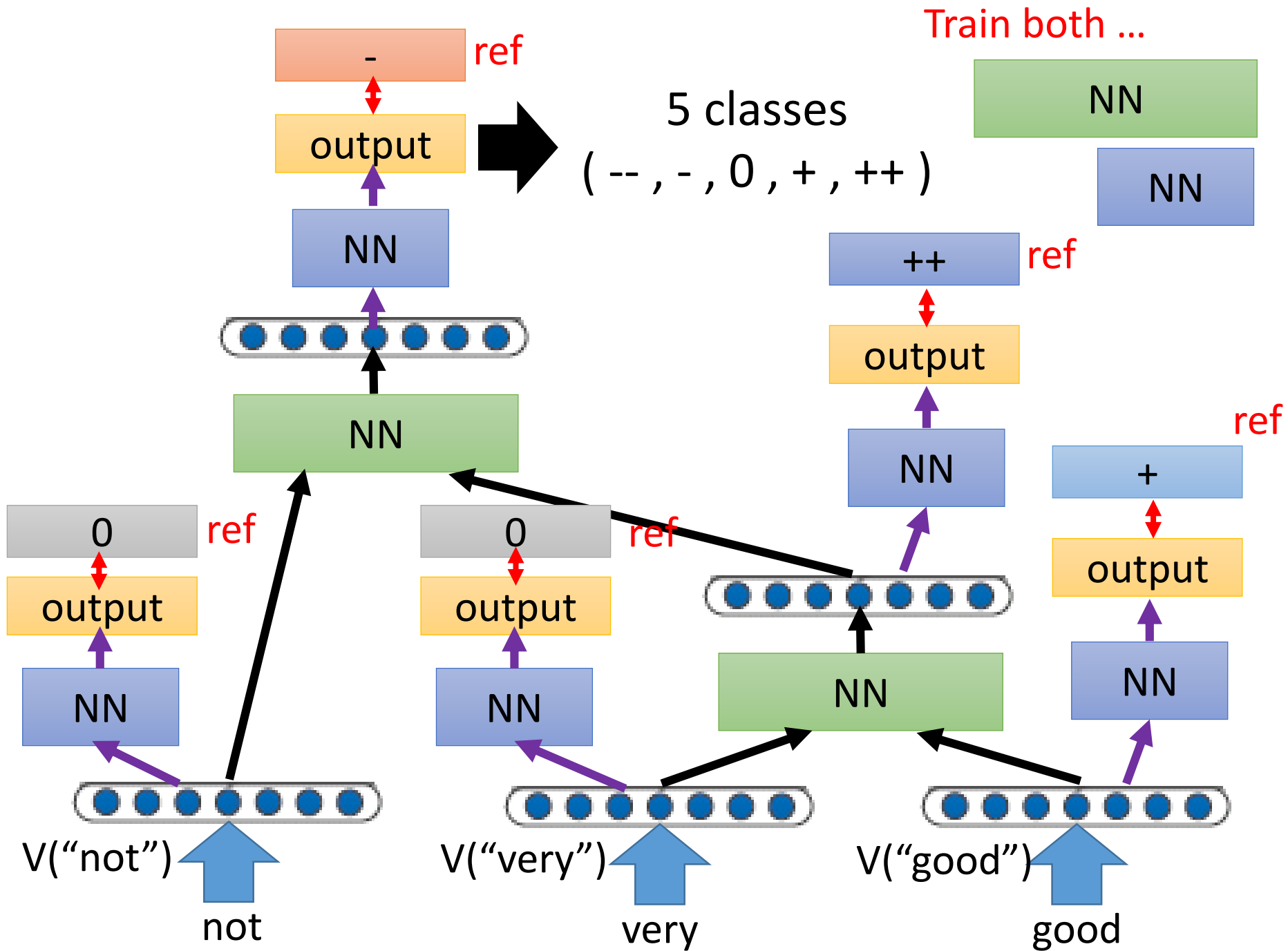




# Training Data

5-class sentiment classification  
( -- , - , 0 , + , ++ )





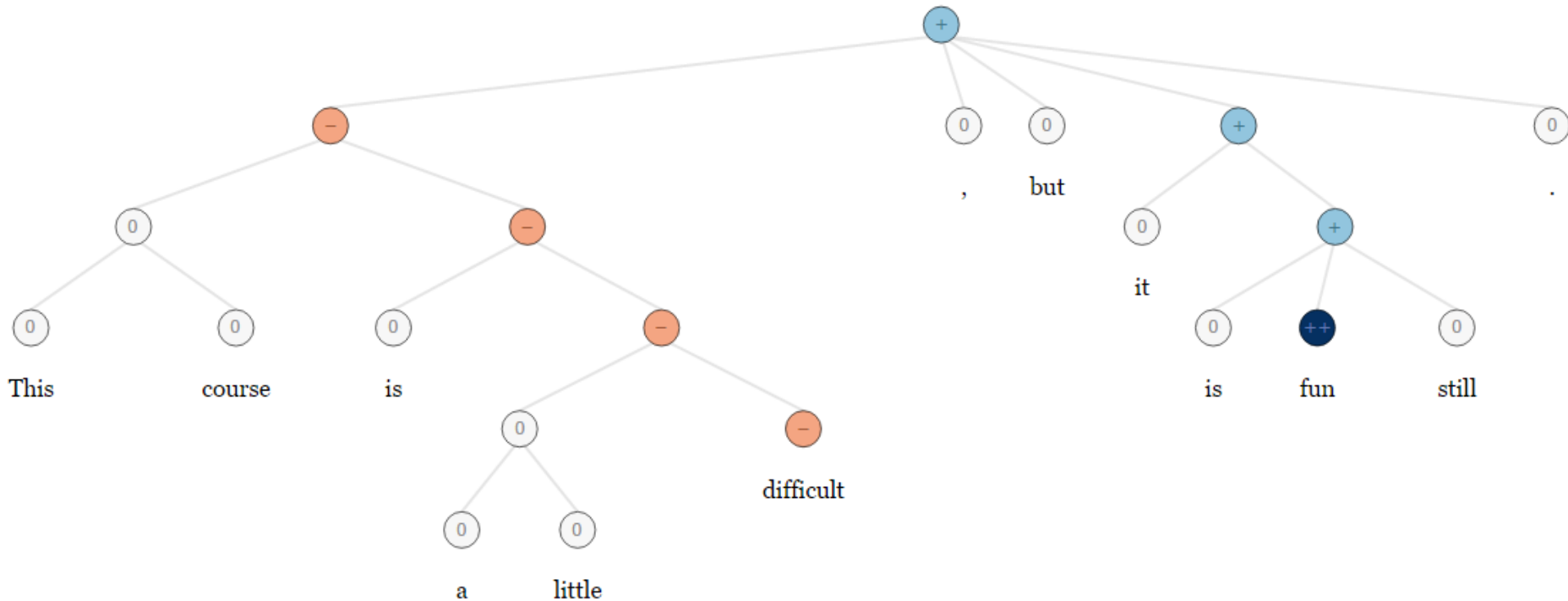
# More ...

## 5-class sentiment classification ( -- , - , 0 , + , ++ )

- Demo

- <http://nlp.stanford.edu:8080/sentiment/rntnDemo.html>

This course is a little difficult, but it is fun still.



# Meaning of Word Sequence

## - Outline

Deep Structured  
Semantic Model  
(DSSM)

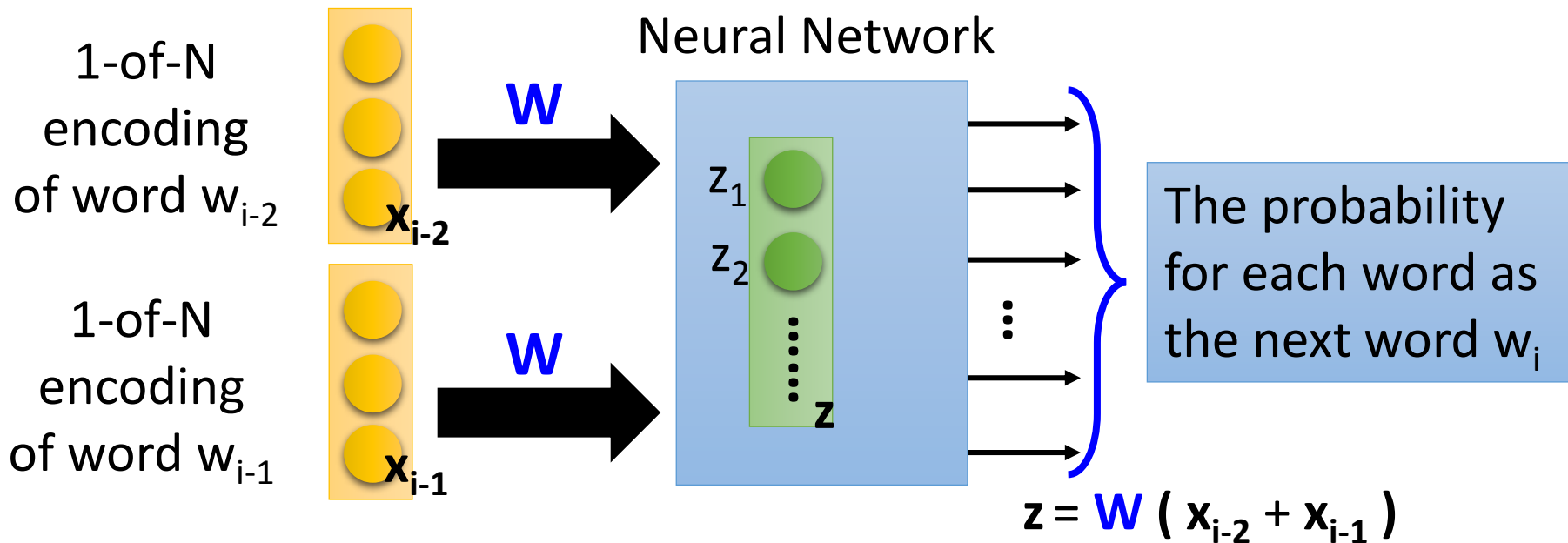
- Application: Information Retrieval (IR)

Recursive Deep  
Model

- Application: Sentiment Analysis

Paragraph Vector

- Unsupervised



Paragraph  $d_1$ : (The paragraph is related to "The lord of the ring")

..... 魔君 名叫 索倫 (Sauron) .....

$w_{i-2}$   $w_{i-1}$   $w_i$

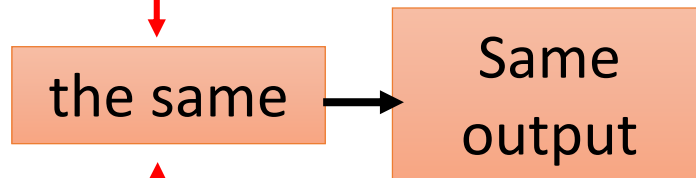
$$z = W (x_{i-2} + x_{i-1})$$

Paragraph  $d_2$ : (The paragraph is related to "仙五")

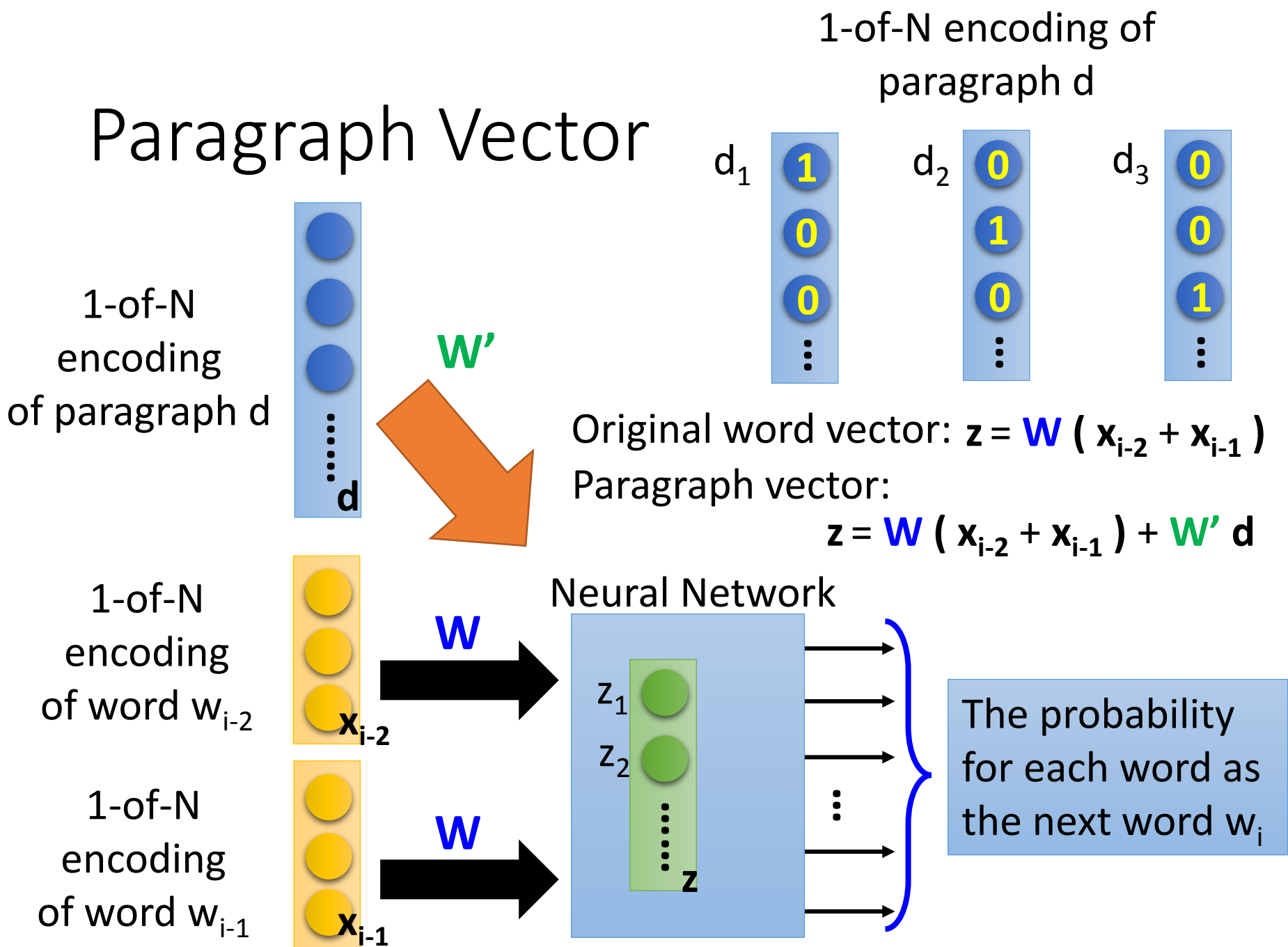
..... 魔君 名叫 姜世離 .....

$w_{i-2}$   $w_{i-1}$   $w_i$

$$z = W (x_{i-2} + x_{i-1})$$



# Paragraph Vector



# Paragraph Vector

Original word vector:

$$z = \mathbf{W} ( \mathbf{x}_{i-2} + \mathbf{x}_{i-1} )$$

Paragraph vector:

$$z = \mathbf{W} ( \mathbf{x}_{i-2} + \mathbf{x}_{i-1} ) + \mathbf{W}' \mathbf{d}$$

Then error of the prediction can be explained by the meaning of the paragraphs.

Paragraph  $d_1$ : (The paragraph is related to "The lord of the ring")

..... 魔君      名叫      索倫 (Sauron)      .....

$W_{i-2}$        $W_{i-1}$        $W_i$

$$z = \mathbf{W} ( \mathbf{x}_{i-2} + \mathbf{x}_{i-1} ) + \mathbf{W}' \mathbf{d}_1$$

Paragraph  $d_2$ : (The document is related to "仙五")

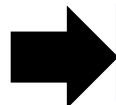
..... 魔君      名叫      姜世離      .....

$W_{i-2}$        $W_{i-1}$        $W_i$

$$z = \mathbf{W} ( \mathbf{x}_{i-2} + \mathbf{x}_{i-1} ) + \mathbf{W}' \mathbf{d}_2$$

different

Paragraph vector of  $d: V(d) = \mathbf{W}' \mathbf{d}$



Meaning of the paragraph

# Meaning of Word Sequence

## - Summary

Deep Structured  
Semantic Model  
(DSSM)

- Application: Information Retrieval (IR)


Recursive Deep  
Model

- Application: Sentiment Analysis

Paragraph Vector

- Unsupervised





Thank You

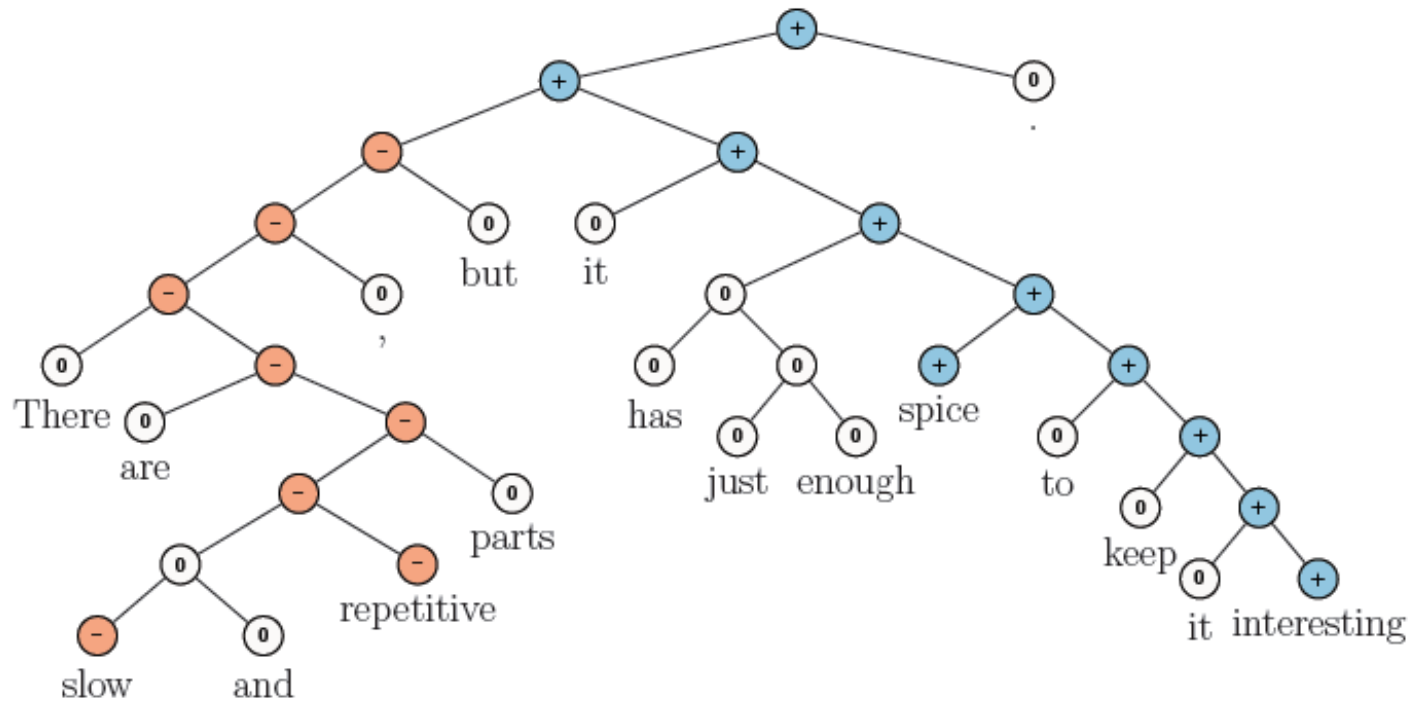
# Appendix

# Chinese Room



[https://www.youtube.com/watch?feature=player\\_embedded&v=0F3-j-GQcts](https://www.youtube.com/watch?feature=player_embedded&v=0F3-j-GQcts)

# Demo in the paper



# More .....

- The paragraph vector can also be used in retrieval
  - Demo: [http://www.logos.t.u-tokyo.ac.jp/~hassy/implementations/paragraph\\_vector/](http://www.logos.t.u-tokyo.ac.jp/~hassy/implementations/paragraph_vector/)
- Toolkit: <https://github.com/klb3713/sentence2vec>

# Word classes

- One of the most successful NLP concepts in practice
- Similar words should share parameter estimation, which leads to generalization
- Example:

$$\begin{aligned} \text{Class}_1 &= (\text{yellow}, \text{green}, \text{blue}, \text{red}) \\ \text{Class}_2 &= (\text{Italy}, \text{Germany}, \text{France}, \text{Spain}) \end{aligned}$$

- Usually, each vocabulary word is mapped to a single class (similar words share the same class)

# Word classes

- There are many ways how to compute the classes – usually, it is assumed that similar words appear in similar contexts
- Instead of using just counts of words, we can use also counts of classes, which leads to generalization (better performance on novel data)

*Class-based n-gram models of natural language* (Brown, 1992)