

1-① Bigram probabilities of the 3rd sentence

calculating bigram probability:

$$P(w_i/w_{i-1}) = \text{count}(w_{i-1}, w_i) / \text{count}(w_{i-1})$$

In english

probability that word<sub>i-1</sub> is followed by word<sub>i</sub>

$$= \frac{\text{num times we saw word}_{i-1} \text{ followed by word}_i}{\text{num times we saw word}_{i-1}}$$

$$[ \text{num times we saw word}_{i-1} ]$$

S = beginning of sentence

IS = end of sentence

$$P(I/S) = 2/3$$

$$P(\text{like}/I) = 1/3$$

$$P(\text{green}/\text{like}) = 1/1 = 1$$

$$P(\text{eggs}/\text{green}) = 1/1 = 1$$

$$P(\text{and}/\text{eggs}) = 2/1 = 1$$

$$P(\text{IS}/\text{and}) = 1/1 = 1$$

② Trigram probability of the 3rd sentence

calculating trigram probability

$$P(w_i/w_{i-1}, w_{i-2}) = \text{count}(w_{i-2}, w_{i-1}, w_i) / \text{count}(w_{i-2}, w_{i-1})$$

In english:

probability that we saw word<sub>i-1</sub> followed by word<sub>i-2</sub>

followed by word<sub>i</sub>

$$= \frac{\text{num times we saw the 3 words together}}{\text{num times we saw word}_{i-1} \text{ followed by word}_{i-2}}$$

$$P(\text{green/like}) = \text{count}(\text{green like}) / \text{count}(\text{like})$$

$$= 0/1 = 0$$

$$P(\text{eggs/like green}) = \text{count}(\text{eggs like green}) / \text{count}(\text{like green})$$

$$= 0/1 = 0$$

$$P(\text{ana/green eggs}) = \text{count}(\text{ana green eggs}) / \text{count}(\text{green eggs})$$

$$= 0/1 = 0$$

$$P(\text{ham/eggs ana}) = \text{count}(\text{ham eggs ana}) / \text{count}(\text{eggs ana})$$

$$= 0/1 = 0$$

## ⑪ word2vec

### ① wordvec model

It is a two-layer neural network that processes the text, input is a text corpus, output is a set of vectors. feature vectors for words in that corpus. Not a deep neural network, but a numerical form that deep net can understand. No similarity is expressed as a  $90^\circ$  angle, total similarity of 1 is a degree angle

$$\text{similarity} = \cos(\theta) = \frac{AB}{\|A\| \|B\|} = \frac{\sum_{i=1}^n A_i B_i}{\sqrt{\sum_{i=1}^n A_i^2} \sqrt{\sum_{i=1}^n B_i^2}}$$

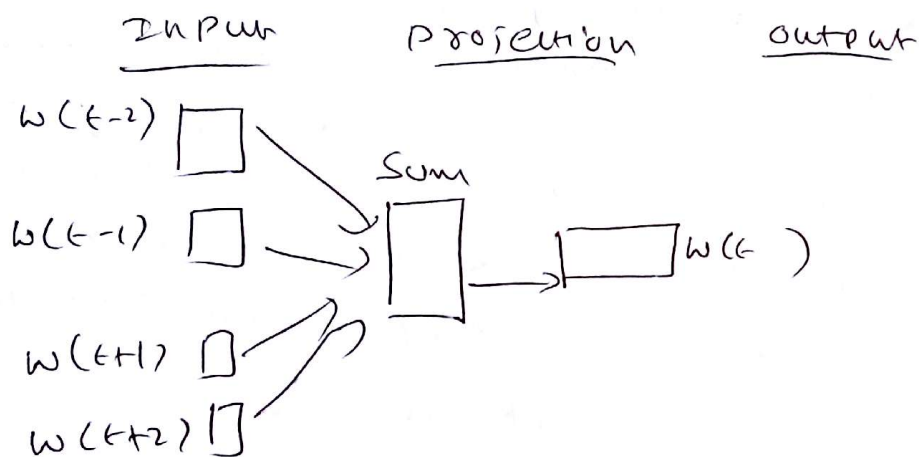
In the model represented in the diagram they have taken a input document and built a wordvec model containing words in the document and found the nearest word using cosine similarity

word2vec can utilize either of two model architecture to produce a distributed representation of word:

- (a) Continuous bag of word
- (b) Continuous skip-gram.

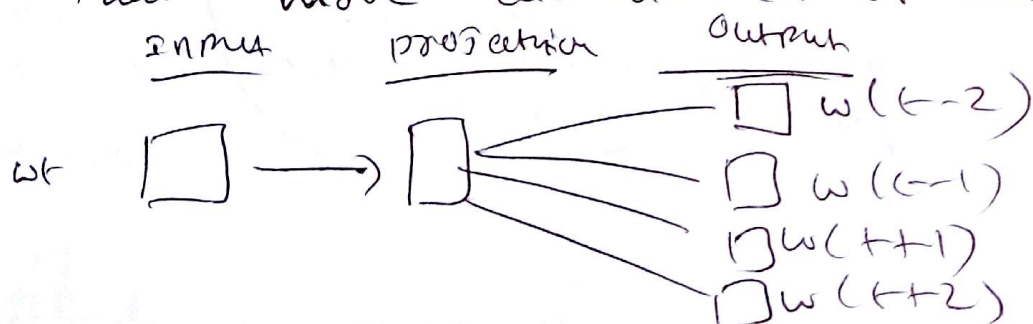
### CBOW

In the continuous bag of word architecture, the model predicts the current word from a window of surrounding context words. The order of context words does not influence prediction.



### Continuous skip-gram

In the continuous skip-gram architecture, the model uses the current word to predict the surrounding window of context words. The skip-gram architecture weighs nearby context words more heavily than more distant context words.





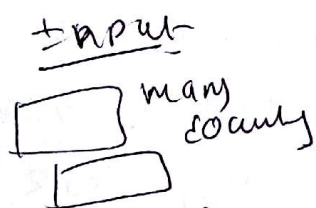
## b) extension of word2vec for multiple documents

An extension of word2vec to construct embeddings from entire documents is called Paragraph 2vec or doc2vec.

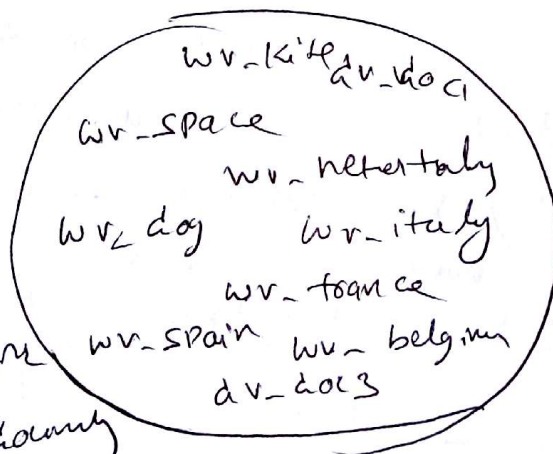
Doc2vec is an unsupervised algorithm to generate vector for sentence / paragraphs / documents. The algorithm is an adaption of word2vec which can generate vector for words.

The vectors generated by doc2vec can be used for tasks like finding similarity between sentences / paragraphs / documents. doc2vec sentence vectors are word order independent. It generates word vectors constructed from character ngrams and then adding up the word vectors to compose a sentence vector. It generates vectors where the vector for a sentence is generated by predicting the adjacent sentence, that are assumed to be semantically related.

### Doc2vec for diagram



training word vectors for each word and each document



most-similar (to name)  
Paris 0.876543  
London 0.76543  
most-similar  
highest cosine  
distance value in  
vector space with  
consideration of the document

## Difference between CBOW and Continuous Skip-gram

- ① In CBOW we need to train task as "predicting the word given its content" where as in the skip-gram we train task as "predicting the content given a word".
- ② Skip-gram works well with small document or for training data, whereas well even rare words or phrases.
- ③ CBOW is a several times faster to train than the skip-gram. Slightly better accuracy for the frequent words.

Given the sentence is "morning fog, afternoon light rain"

Skip-gram word2vec model for above sentence is

consider the sentence:-

morning fog, afternoon light rain,

consider window size is 1

Input  
morning  
fog  
afternoon

light

rain

Training samples

(morning, fog), (morning, afternoon)

(fog, morning) (fog, afternoon)

(afternoon, morning) (afternoon, fog)

(afternoon, light) (afternoon, rain)

(light, morning) (light, fog) (light, afternoon)

(light, rain)

(rain, morning) (rain, fog) (rain, afternoon)

(rain, light)

we need to build a vocabulary of words  
(morning, fog, afternoon, light, rain)

consider input is fog then vector representation is  
(0, 1, 0, 0, 0)

Similarly the vector representation for morning, afternoon and light are as follows, because these are in the context of that particular input word.

morning: (1, 0, 0, 0, 0)

afternoon: (0, 0, 1, 0, 0)

light = (0, 0, 0, 1, 0)

