



Inspire...Educate...Transform.

# Word embeddings

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# Text processing

***Words and sentences are of varying length, is this a problem for using them as input to a machine learning algorithm?***

Images have pixel intensities which can act as direct inputs to a neural network.

While text needs to be encoded into a vector form.

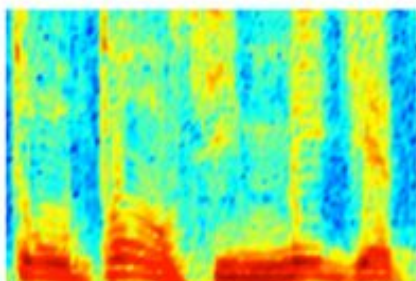
Popular methods for generating word embeddings:

Word2Vec - Mikolov, Tomas; et al. "Efficient Estimation of Word Representations in Vector Space

GloVe - <http://nlp.stanford.edu/projects/glove/>

# Text processing

## AUDIO



Audio Spectrogram

DENSE

## IMAGES

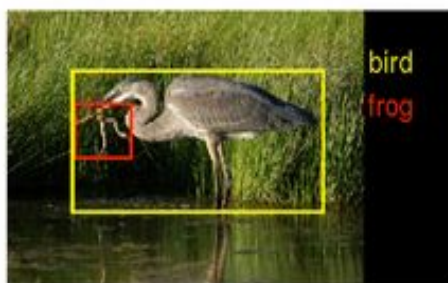


Image pixels

DENSE

## TEXT

0	0	0	0.2	0	0.7	0	0	0	...	...
---	---	---	-----	---	-----	---	---	---	-----	-----

Word, context, or document vectors

SPARSE

# Learning word embeddings

## *Word2Vec and GloVe*

- Unsupervised learning neural network based algorithms for obtaining vector representations for words.
- Trained on large corpus of text data.
- representations showcase interesting linear substructures of the word vector space.
- Generates a fixed length vector embedding for each word.

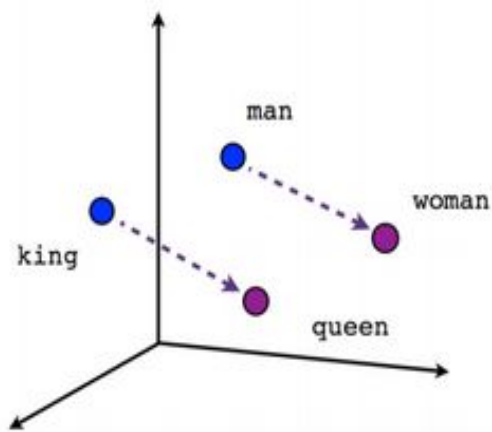
If the length of a given sentence is  $s$ , then the dimensionality of the sentence matrix is  $s \times d$  (where  $d$  is the word2vec dimensions).

The parameter  $d$  can be in range of 100 to 1000, typically. This is decided when training the unsupervised models (*Word2Vec* or *GloVe*).

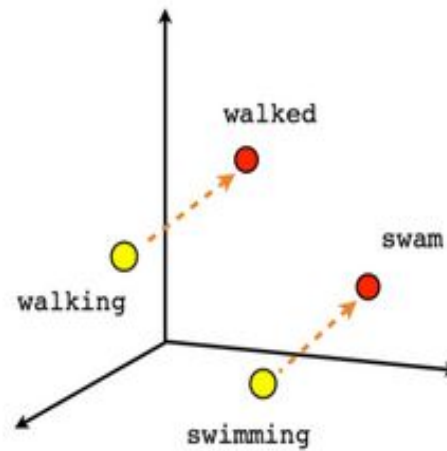
# Word2Vec

- Word2vec is a group of related models that are used to produce word embeddings.
- 
- Word2vec was created by a team of researchers led by Tomas Mikolov at Google.
- 
- Algorithm uses a large amount of text to create high-dimensional (50 to 300 dimensional) representations.
- 
- representations of words capturing relationships between words unaided by external annotations.
- 
- Captures many linguistic regularities,
- $\text{vec}(\text{'Rome'}) = \text{vec}(\text{'Paris'}) - \text{vec}(\text{'France'}) + \text{vec}(\text{'Italy'})$ .

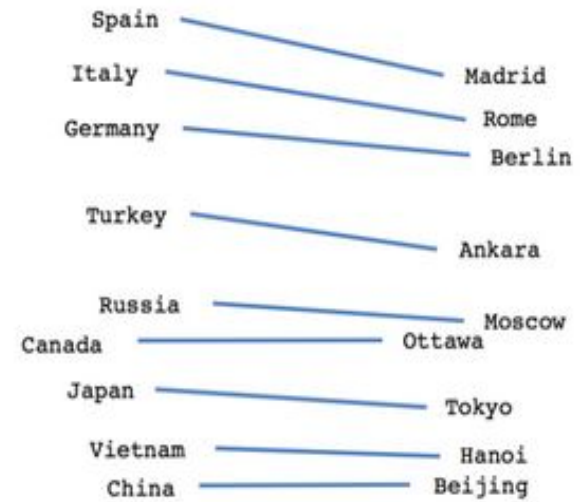
# Word2Vec



Male-Female



Verb tense



Country-Capital

## Word2Vec: Skip-Gram Model

- A single hidden layer neural network is trained to perform a fake task.
- After training the fake task is dumped and only hidden weights are used.
- Fake Task: Given a sentence,

“The quick brown fox jumps over the lazy dog.”

Predict the probabilities of different words from vocabulary occurring in a fixed window size around the chosen word.

# Word2Vec: Skip-Gram Model

## Source Text

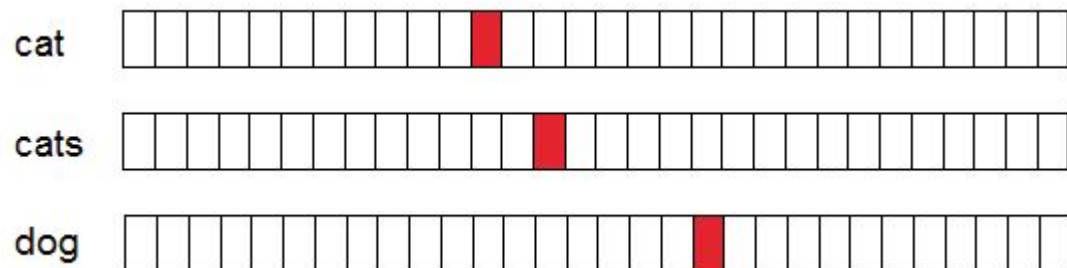
## Training Samples

The quick brown fox jumps over the lazy dog. →	(the, quick) (the, brown)
The quick brown fox jumps over the lazy dog. →	(quick, the) (quick, brown) (quick, fox)
The quick brown fox jumps over the lazy dog. →	(brown, the) (brown, quick) (brown, fox) (brown, jumps)
The quick brown fox jumps over the lazy dog. →	(fox, quick) (fox, brown) (fox, jumps) (fox, over)

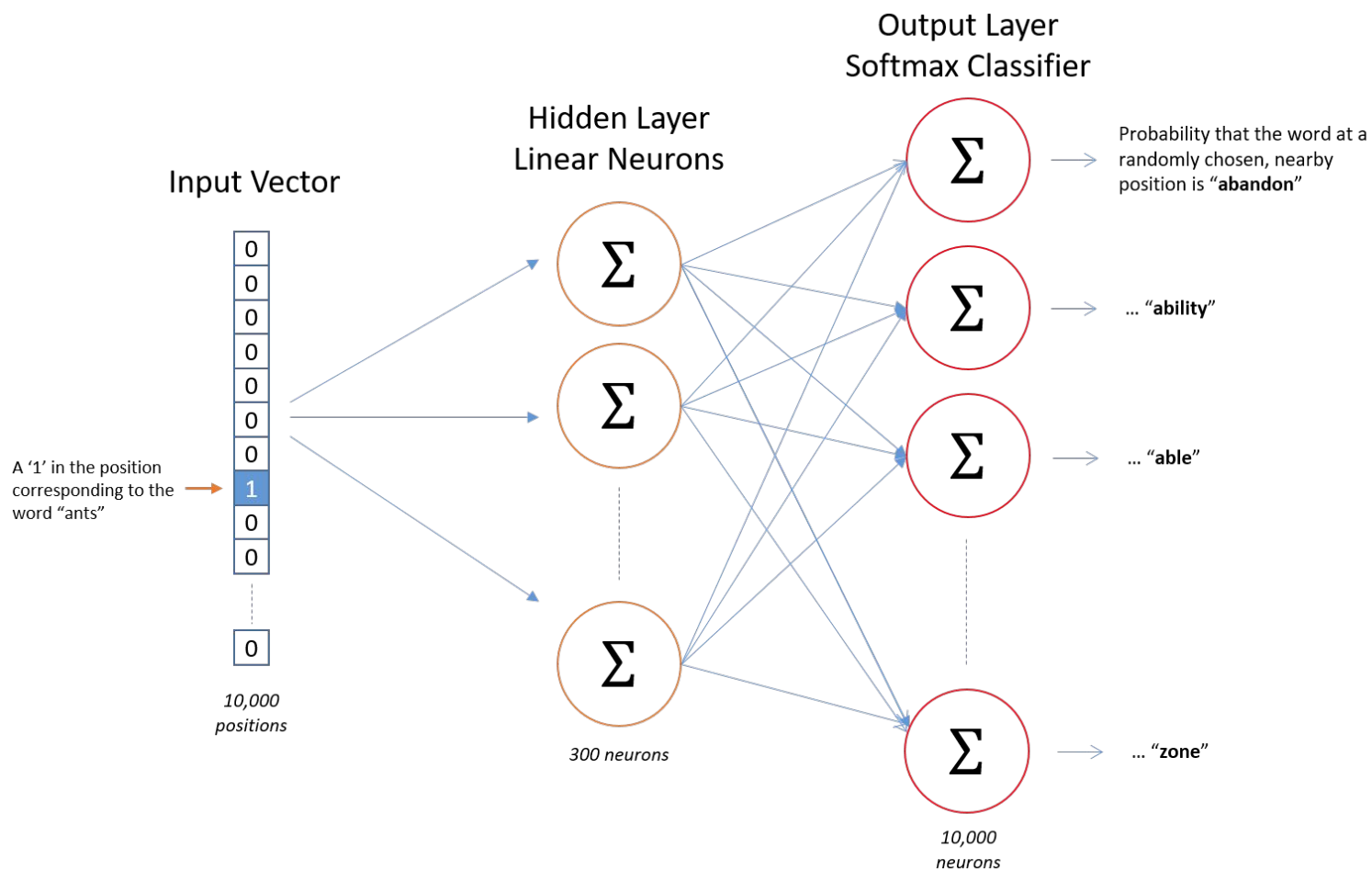


## • One hot encoding of a word:

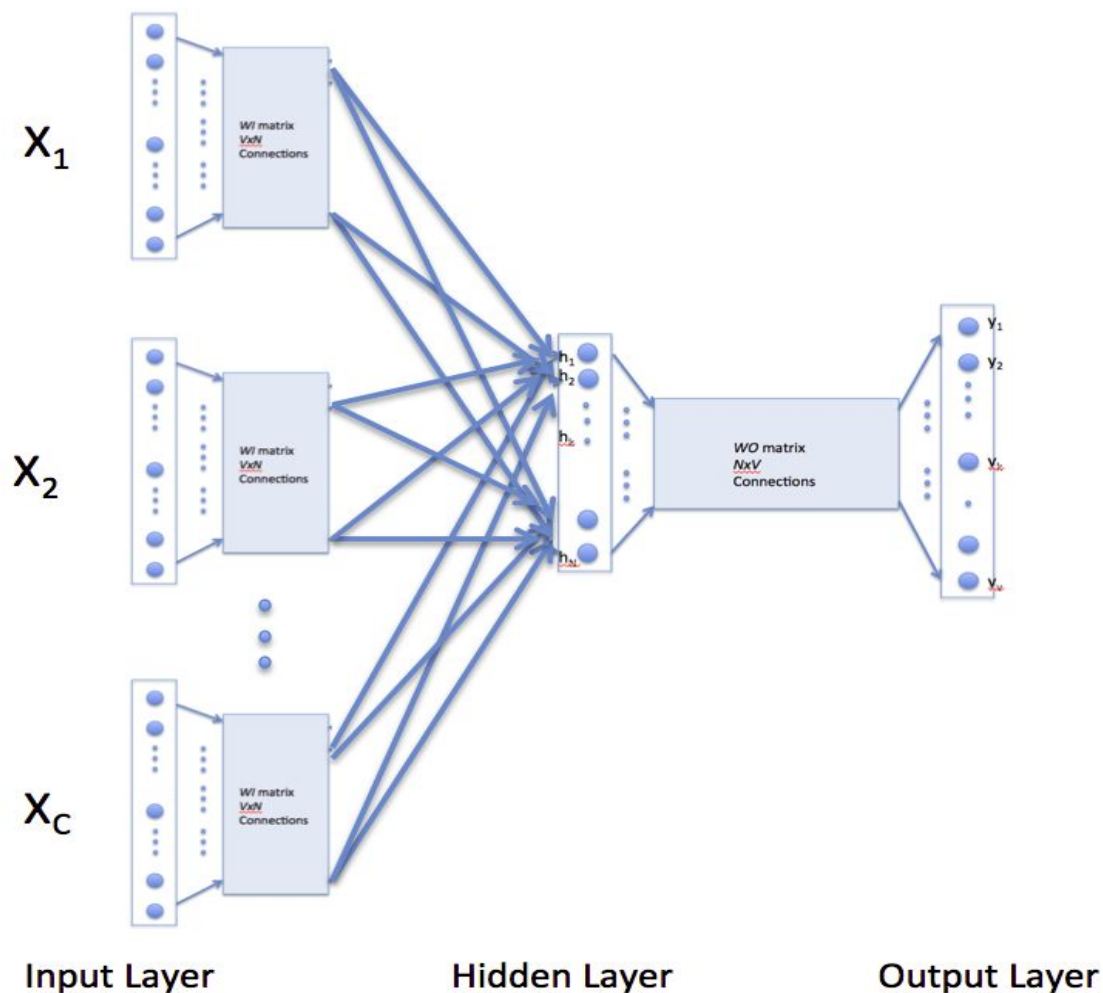
- 
- We need a numerical representation for each word to train our skip-gram model.
- If you have a vocabulary of 10000 words treat each word as a state of categorical variable and dummify it.



# Word2Vec: Skip-Gram Model



# Word2Vec: CBOW



**Training sample:**

Given Sentence:

“The quick brown fox  
jumps over the lazy dog”

(quick,brown,jumps:fox)

(jumps,the,dog: lazy)



## Skip-gram Vs CBOW

- Skip-gram: works well with small amount of the training data, represents well even rare words or phrases.
- 
- CBOW: several times faster to train than the skip-gram, slightly better accuracy for the frequent words

<https://code.google.com/archive/p/word2vec/>



# GloVe: Global Vectors for Word Representation

Jeffrey Pennington, Richard Socher, and Christopher D. Manning. 2014

# GloVe

- GloVe is an unsupervised learning algorithm for obtaining vector representations for words.
- 
- Training is performed on aggregated global word-word co-occurrence statistics from a corpus
- 
- Resulting representations showcase interesting linear substructures of the word vector space.

# GloVe

- Sometimes, the nearest neighbors according to this metric reveal rare but relevant words that lie outside an average human's vocabulary.
- 
- For example, here are the closest words to the target word frog:
- 
- Frog, frogs, toad, litoria, leptodactylidae, rana, lizard, eleutherodactylus



3. litoria



4. leptodactylidae

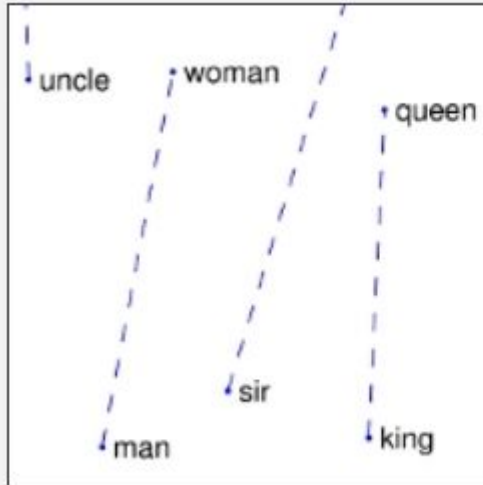


5. rana

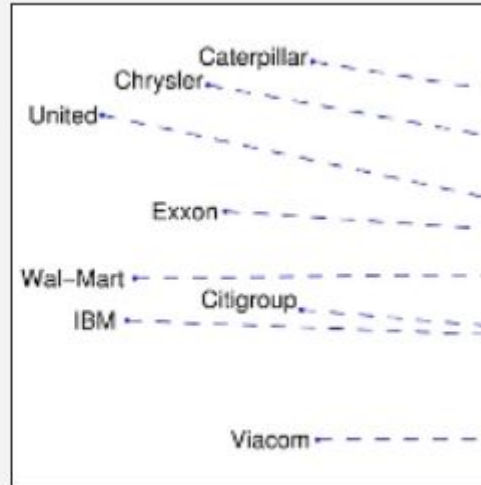


7. eleutherodactylus

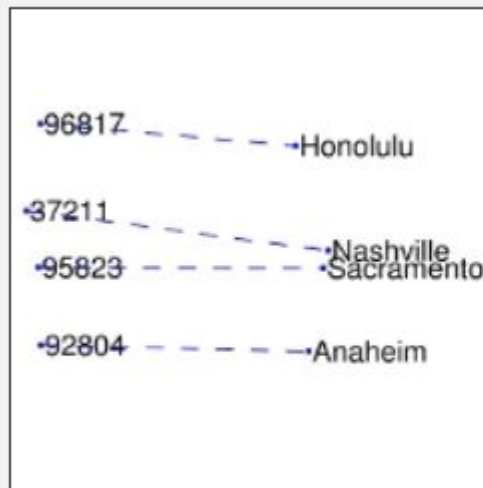
# GloVe



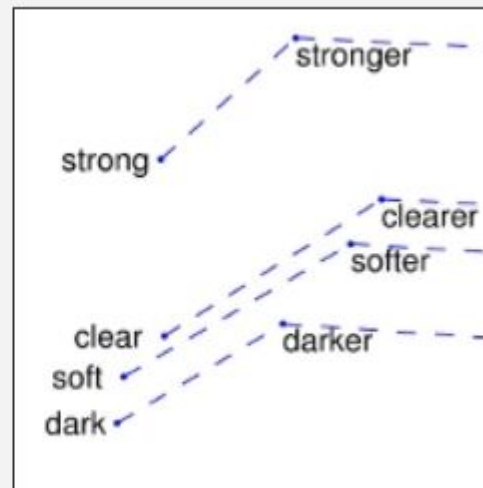
man - woman



company - ceo



city - zip code



comparative - superlative

Linear substructures: The similarity metrics used for nearest neighbor evaluations produce a single scalar that quantifies the relatedness of two words



# GloVe: Training

- The GloVe model is trained on the non-zero entries of a global word-word co-occurrence matrix.
- tabulates how frequently words co-occur with one another in a given corpus
- For large corpora, this pass can be computationally expensive, but it is a one-time up-front cost.

# GloVe: Training

- Define a constraint,

$$w_i w_j + b_i + b_j = \log(X_{ij})$$

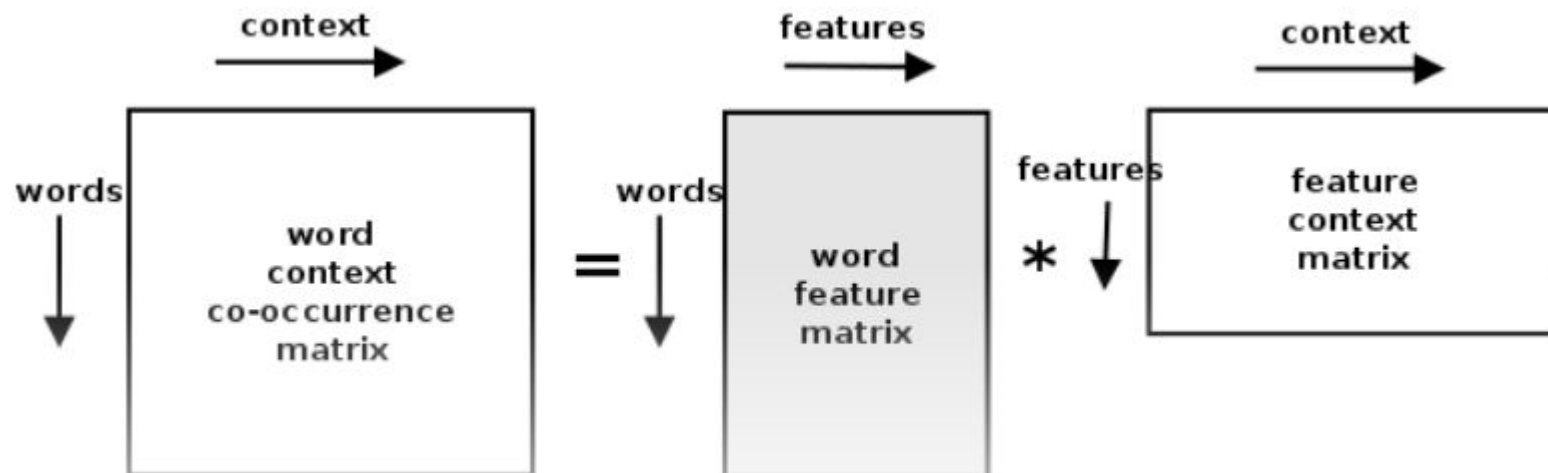
- Now we need a cost function to optimize,

$$J = \sum_{i=1}^V \sum_{j=1}^V f(X_{ij})(w_i^T w_j + b_i + b_j - \log X_{ij})^2$$

$$f(X_{ij}) = \begin{cases} \left(\frac{X_{ij}}{X_{MAX}}\right)^\alpha & \text{if } X_{ij} < X_{MAX} \\ 1 & \text{otherwise} \end{cases}$$

# GloVe: Training

- Training objective of GloVe is to learn word vectors such that their dot product equals the logarithm of the words' probability of co-occurrence.





# GloVe Vs Word2Vec

- In word2vec, Skip-gram models tries to capture co-occurrence one window at a time
- In Glove it tries to capture the counts of overall statistics how often its appears.
- Both capture linear substructures and tend to perform equally good.



# Sentence/Paragraph/Document 2 Vec

# PV-DM model

- Introduced by Tomas Mikolov  
(<https://arxiv.org/pdf/1405.4053v2.pdf>)
- Based on simple idea of using the word2vec (CBOW) model, and adding another vector (Paragraph ID below) to the input.

# PV-DM model

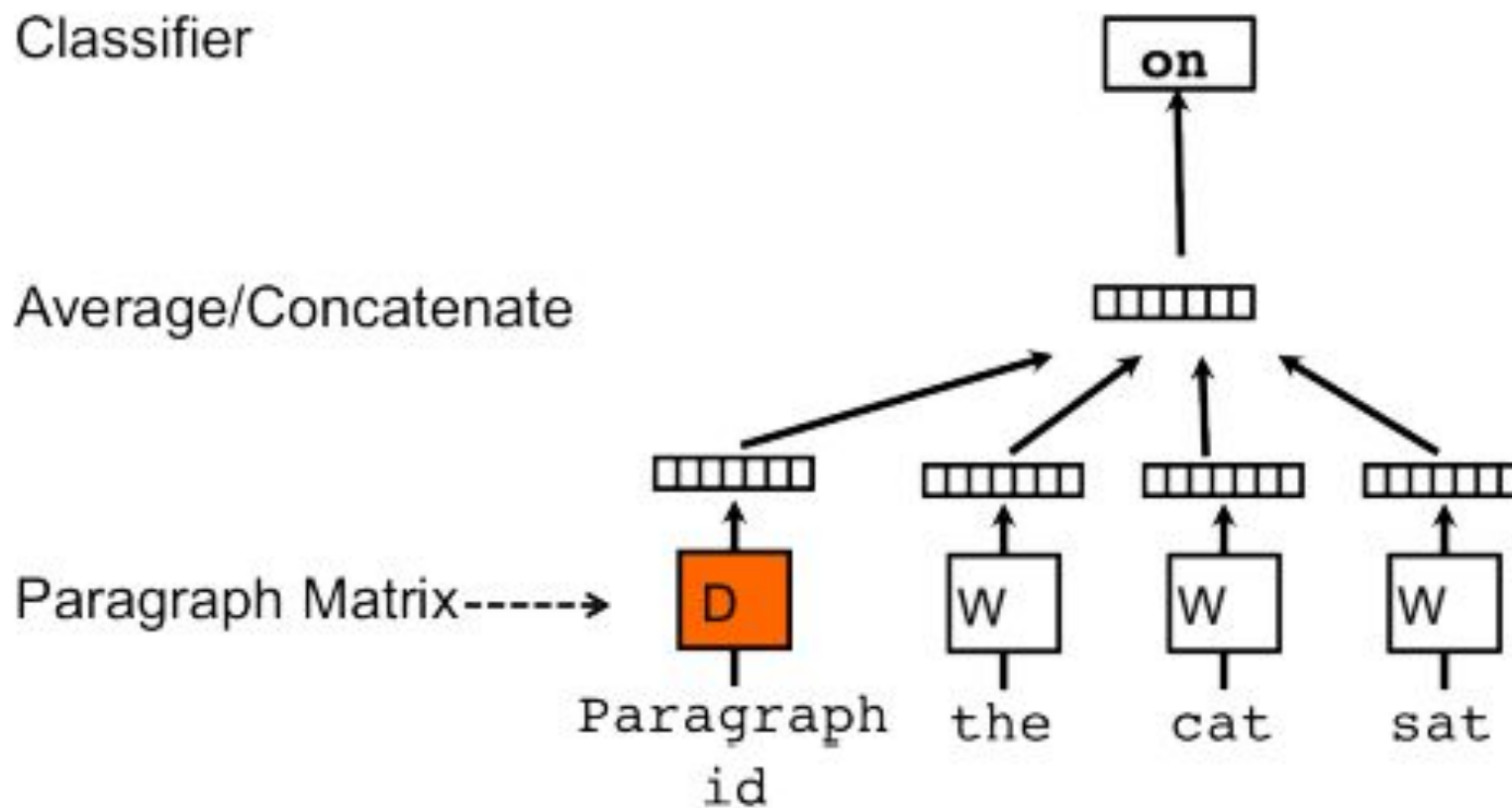


fig 3: PV-DM model

# PV-DBOW model

- Introduced by Tomas Mikolov  
(<https://arxiv.org/pdf/1405.4053v2.pdf>)
- Another way is to ignore the context words in the input, but force the model to predict words randomly sampled from the paragraph in the output



# PV-DBOW model

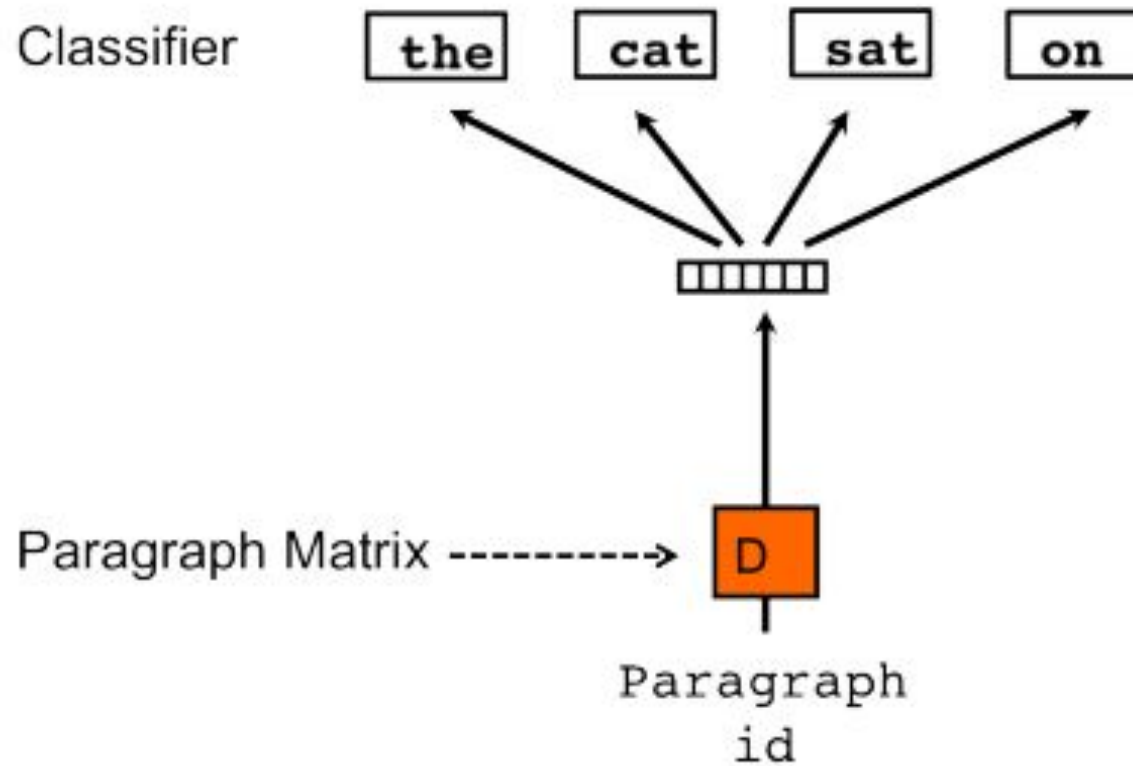


fig 4: PV-DBOW model