

# Deep Learning for Natural Language Processing

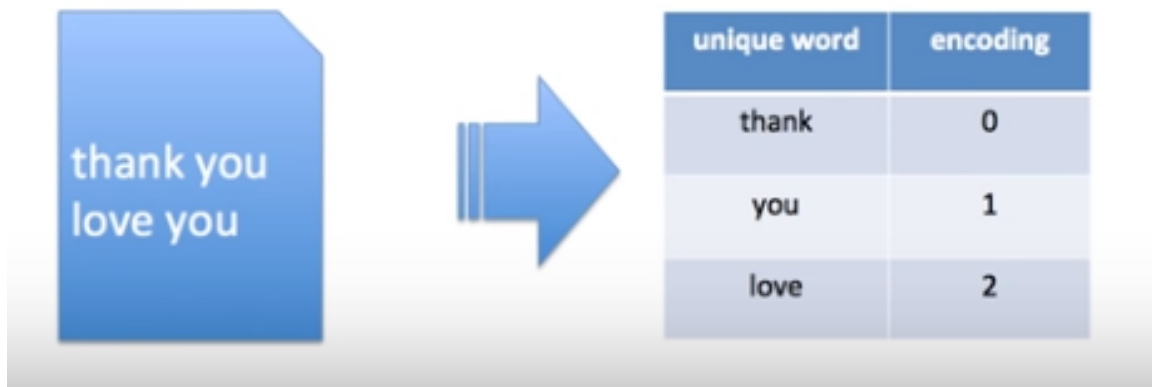
- NLP problems employed shallow machine learning models and time-consuming, hand-crafted features.
- Recent popularity and success of word embeddings neural-based models have achieved superior results.

# Deep Learning for Natural Language Processing

- Can text be input in Deep Learning?
  - NO
- Can number be input in Deep Learning?
  - Yes

# What is word encoding?

Convert text to number



# Vector Representation of Text

What is One Hot Encoding ? Convert text to Vector

	thank	you	love
thank	1	0	0
you	0	1	0
love	0	0	1



unique word	encoding
thank	[1, 0, 0]
you	[0, 1, 0]
love	[0, 0, 1]

# Vector Representation of Text

One Hot Encoding doesn't have **similarity**



unique word	encoding
thank	[1, 0, 0]
you	[0, 1, 0]
love	[0, 0, 1]

# Vector Representation of Text

One Hot Encoding doesn't have **similarity**

cosine similarity also 0 since angle is 90 degree



unique word	encoding
thank	[1, 0, 0]
you	[0, 1, 0]
love	[0, 0, 1]

# Vector Representation of Text

## Embedding

Embedding is dense vector with similarity

unique word	encoding	embedding
king	[1, 0, 0, 0]	[1, 2]
man	[0, 1, 0, 0]	[1, 3]
queen	[0, 0, 1, 0]	[5, 1]
woman	[0, 0, 0, 0]	[5, 3]



# Word2vec approach to represent the meaning of word

- Represent each word with a low-dimensional vector
- Word similarity = vector similarity
- Key idea: Predict surrounding words of every word

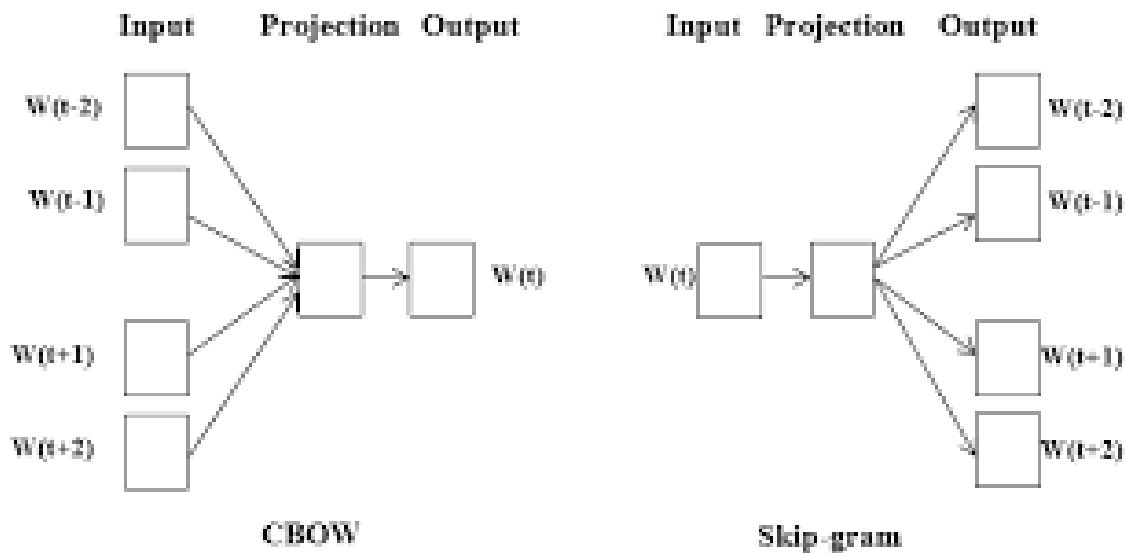


# Represent the meaning of word – word2vec

There are 2 basic neural network models:

- Continuous Bag of Word (CBOW): use a window of word to predict the middle word
- Skip-gram (SG): use a word to predict the surrounding ones in window.

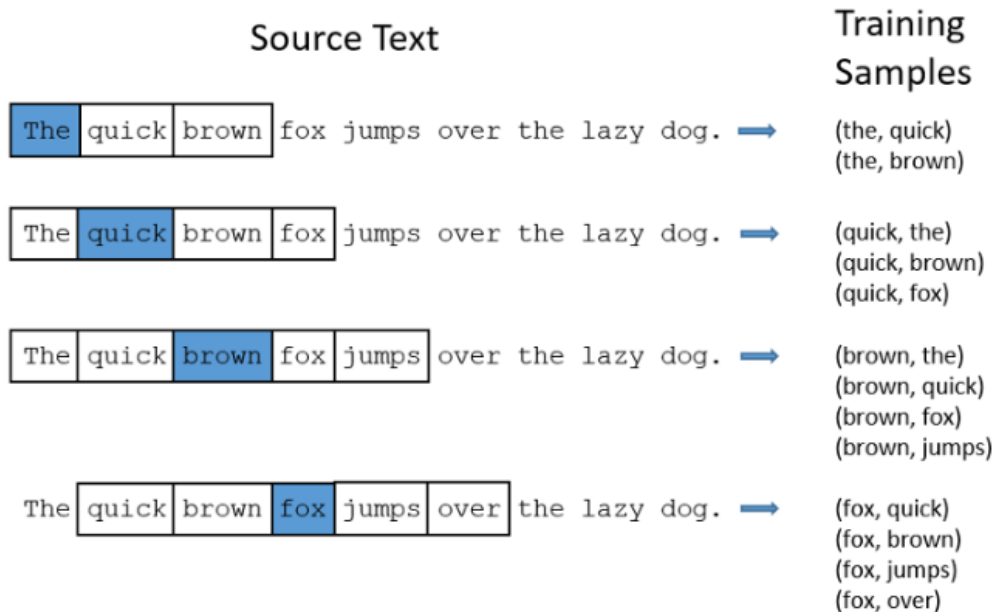
# The Continuous Bag Of Words and the Skip Gram Model



# How word2vec works:

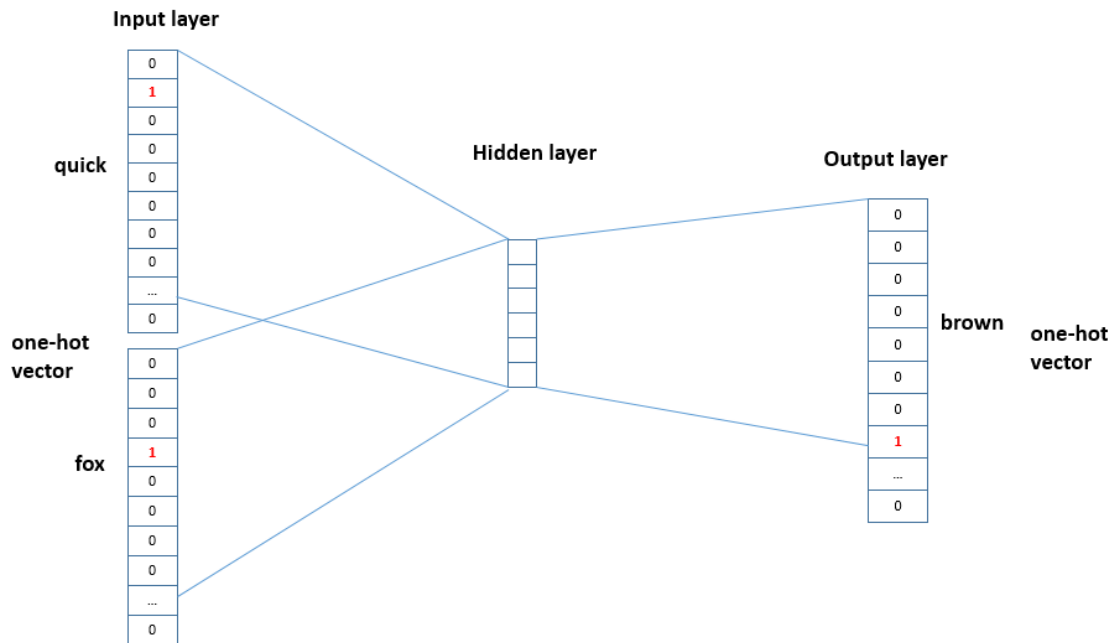
- Take a 3 layer neural network. (1 input layer + 1 hidden layer + 1 output layer)
- Feed it a word and train it to predict its neighbouring word.
- Remove the last (output layer) and keep the input and hidden layer.
- Now, input a word from within the vocabulary. The output given at the hidden layer is the ‘word embedding’ of the input word.

# How word2vec works:

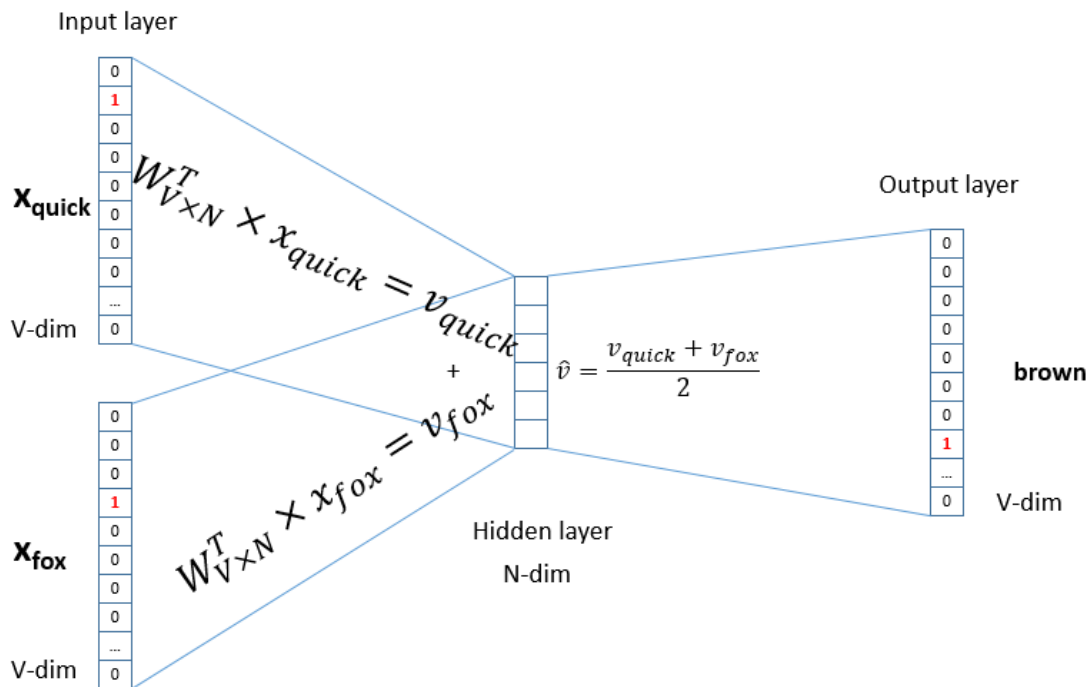


A training sample generation with a window size of 2.

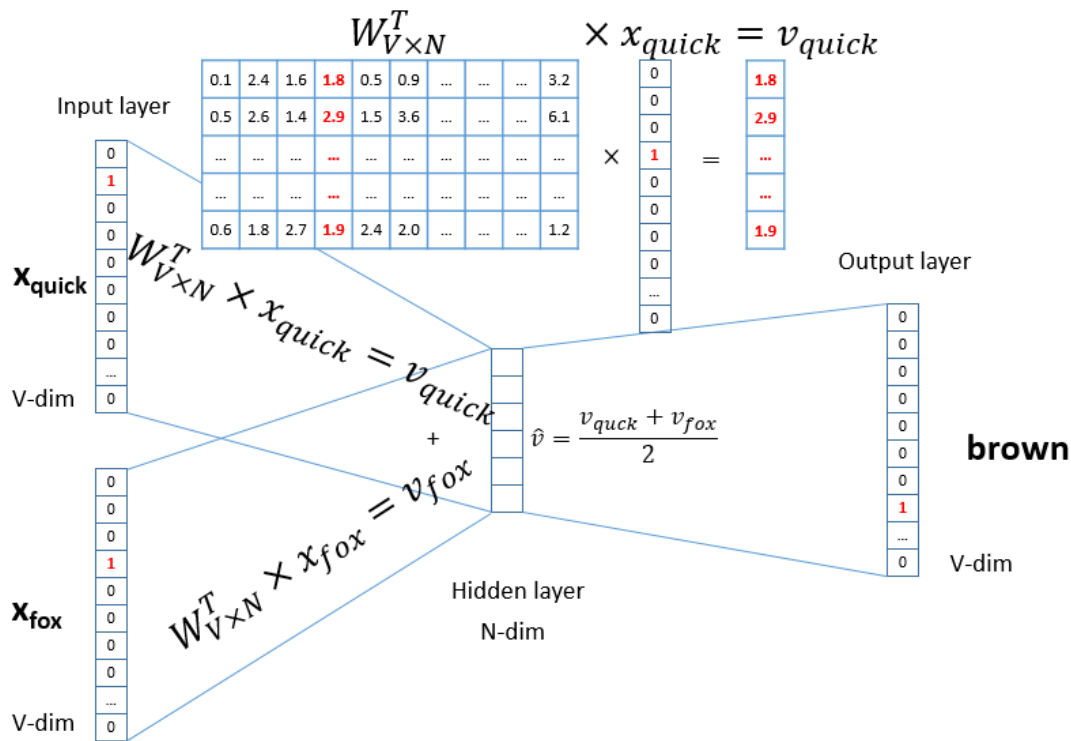
# How word2vec works:



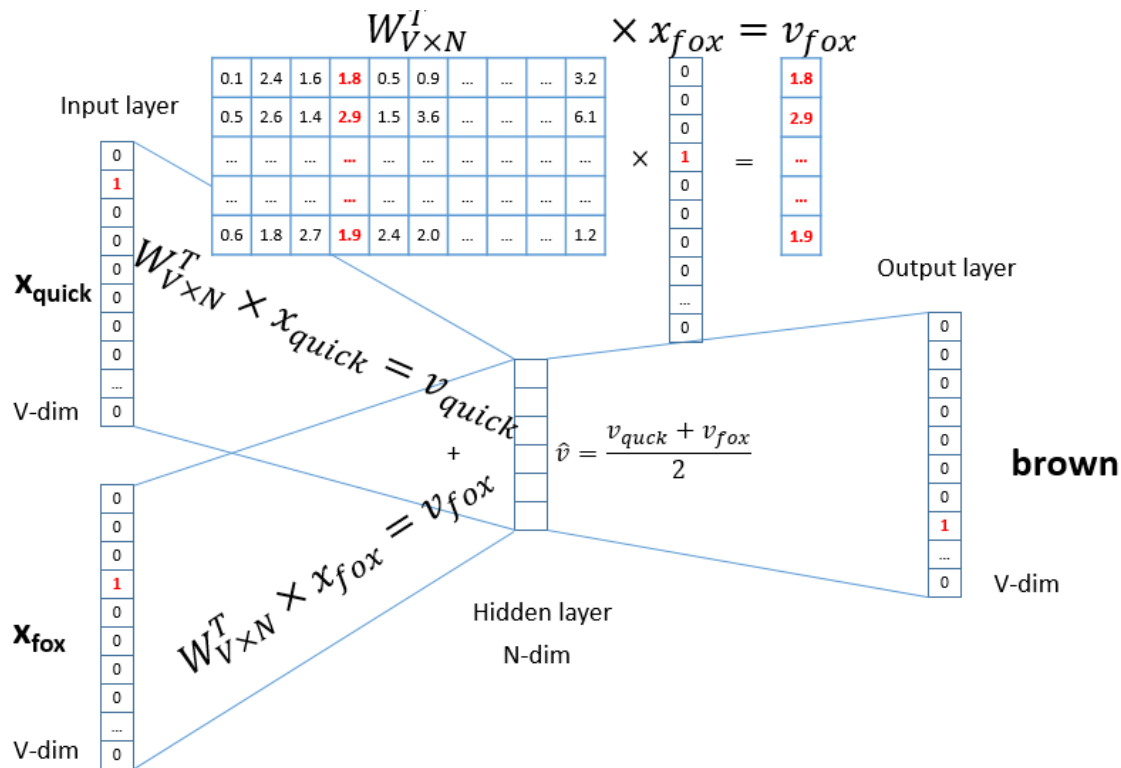
# How word2vec works:



# How word2vec works:

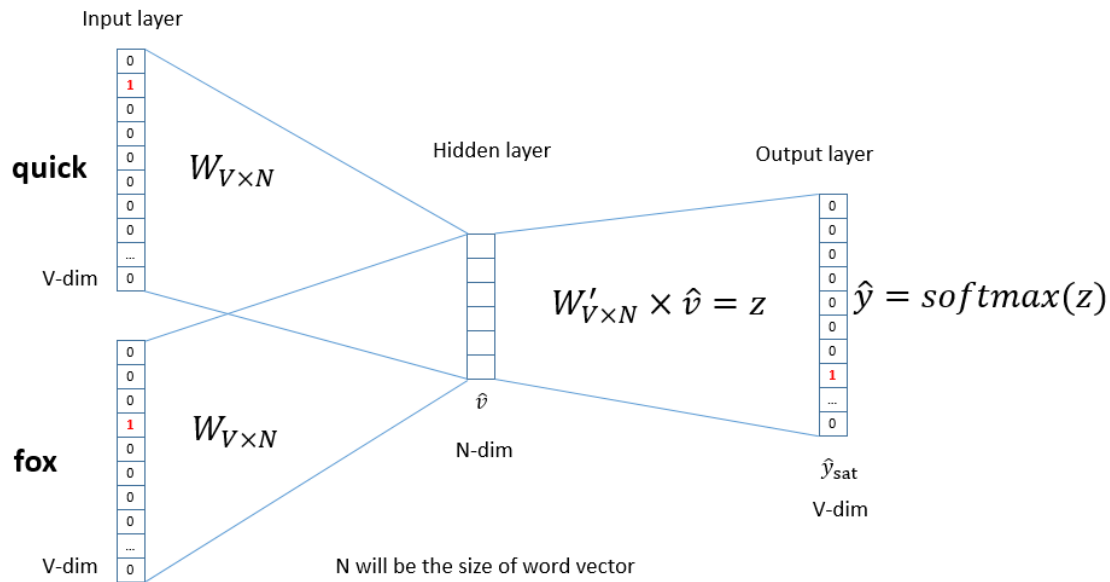


# How word2vec works:

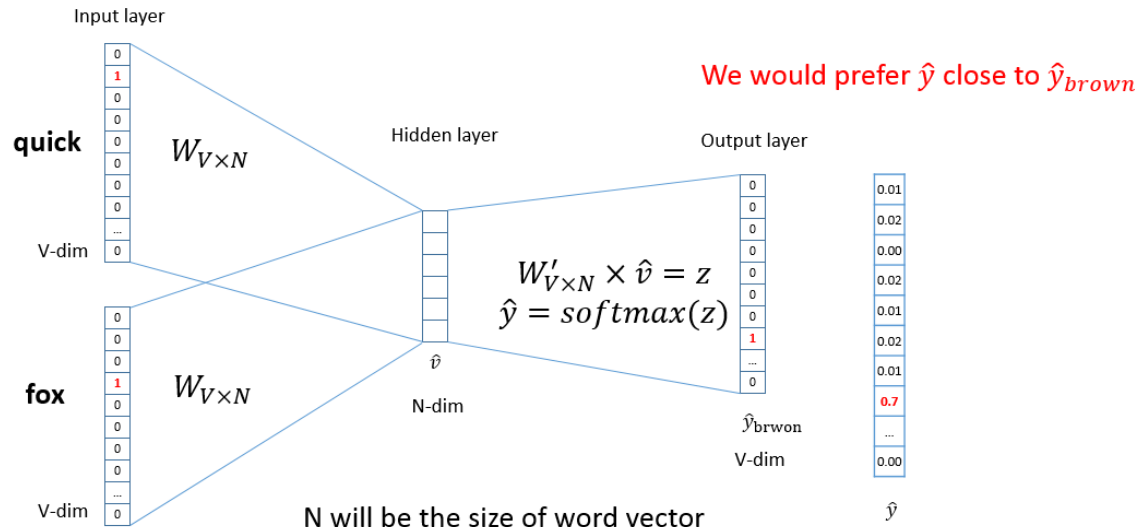




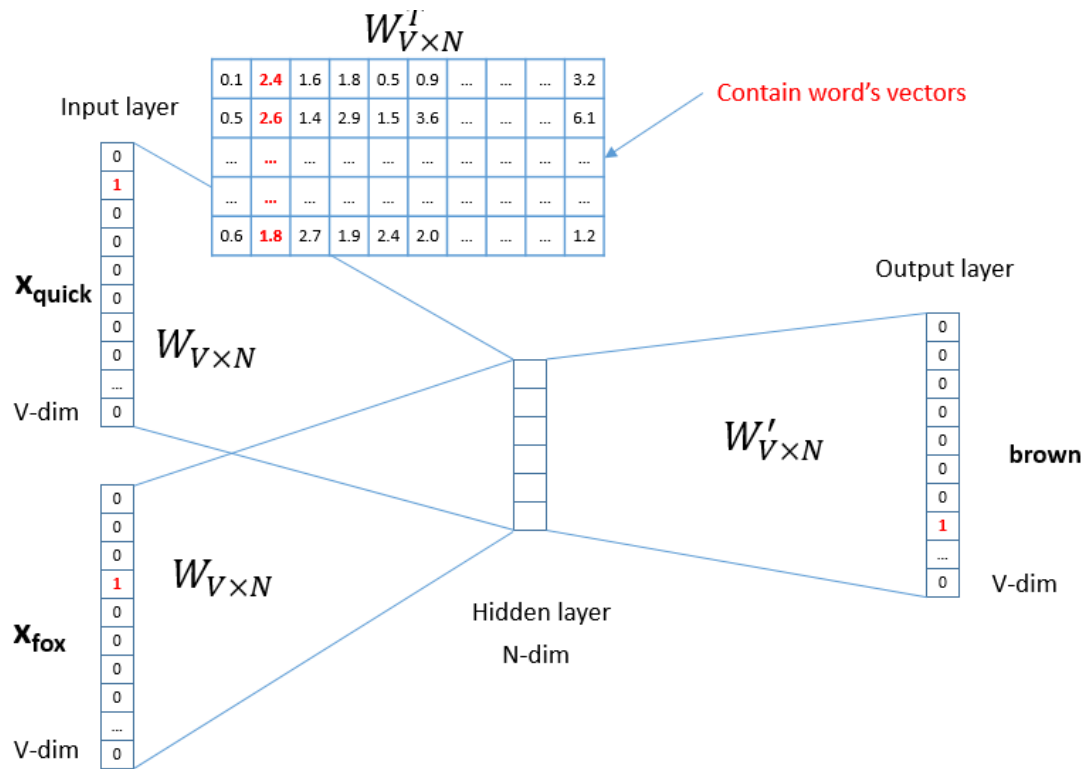
# How word2vec works:



## How word2vec works:



# How word2vec works:



# Implementation using Tensorflow

Step 1

Collect Data

Step 2

Data Preprocessing-  
Remove stop words

Step 3

Generate label for each  
word using skip gram

Step 4

Define Tensorflow Graph

Step 5

Learn Parameters

# Collect Data

```
corpus = ['king is a strong man',  
          'queen is a wise woman',  
          'boy is a young man',  
          'girl is a young woman',  
          'prince is a young king',  
          'princess is a young queen',  
          'man is strong',  
          'woman is pretty',  
          'prince is a boy will be king',  
          'princess is a girl will be queen']
```

king strong man  
queen wise woman  
boy young man  
girl young woman  
prince young king  
princess young queen  
man strong  
woman pretty  
prince boy king  
princess girl queen

# Unique words in the corpus

```
{ 'boy',  
  'girl',  
  'king',  
  'man',  
  'pretty',  
  'prince',  
  'princess',  
  'queen',  
  'strong',  
  'wise',  
  'woman',  
  'young' }
```

# Generate Context word

['king', 'strong']

['king', 'man']

['strong', 'king']

['strong', 'man']

['man', 'king']

['man', 'strong']

['queen', 'wise']

['queen', 'woman']

['wise', 'queen']

['wise', 'woman']

['woman', 'queen']



# Collect Data

	<b>input</b>	<b>label</b>
<b>0</b>	king	strong
<b>1</b>	king	man
<b>2</b>	strong	king
<b>3</b>	strong	man
<b>4</b>	man	king

# Collect Data

```
[[0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 1. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 1. 0. 0. 0. 0. 0. 0. 0. 0. 0. 0.]
 [0. 0. 0. 0. 0. 0. 0. 0. 0. 1. 0. 0.]
```

# References

- Distributed Representations of Words and Phrases Tomas Mikolov and their Compositionality
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- The best “word2vec Parameter Learning Explained”, Xin Rong  
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- Word2Vec Tutorial - The Skip-Gram Model  
<http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/>
- <https://www.youtube.com/watch?v=64qSgA66P-8>
- <https://github.com/minsuk-heo/>