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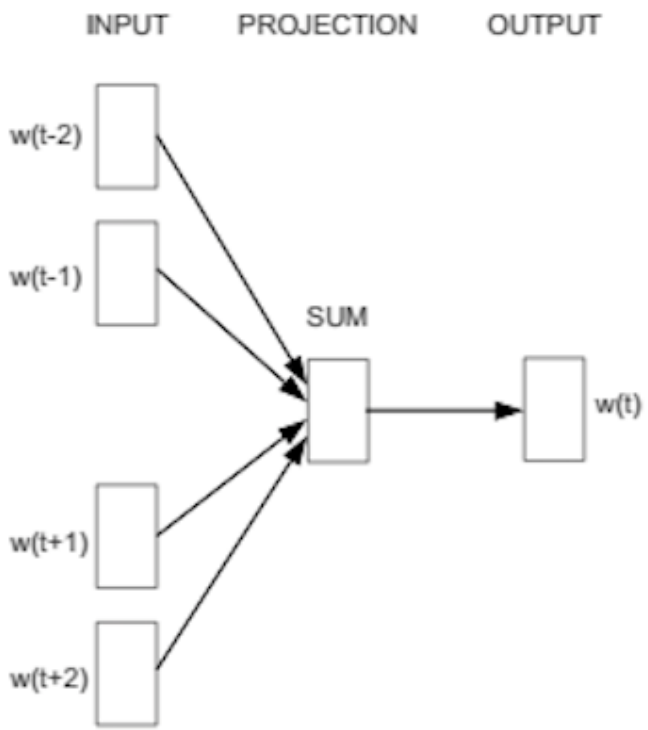
Word Vector

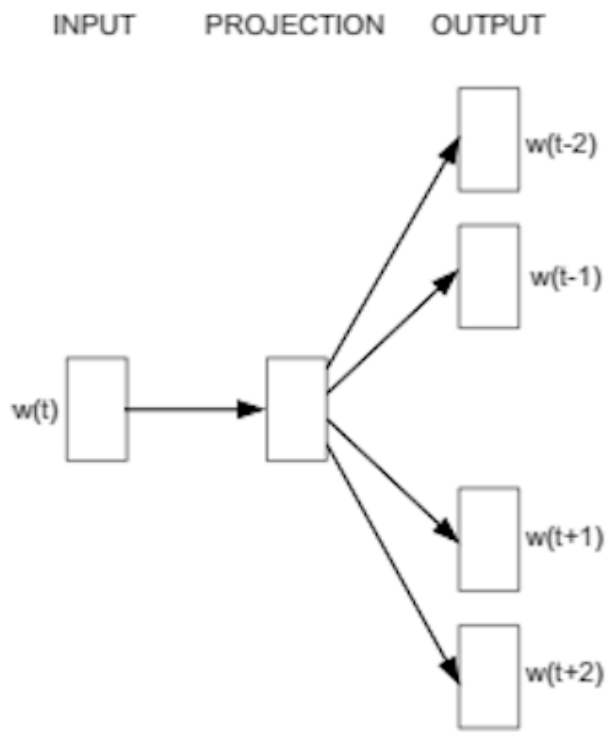
- it’s simply a vector of weights. In a simple 1-of-N (or ‘one-hot’) encoding every element in the vector is associated with a word in the vocabulary. The encoding of a given word is simply the vector in which the corresponding element is set to one, and all other elements are zero.
- Suppose our vocabulary has only five words: King, Queen, Man, Woman, and Child. We could encode the word ‘Queen’ as: [0,1,0,0,0] for [King, Queen, Man, Woman, and Child]

Word2vec

- Word2vec is a two-layer neural net that processes text. Its input is a text corpus and its output is a set of vectors: feature vectors for words in that corpus. It was introduced in 2013 by team of researchers led by Tomas Mikolov at Google.
- Word2vec is a prediction based model rather than frequency. It uses predictive analysis to make a weighted guess of a word co-occurring with respect to it’s neighbouring words. There are 2 variants to this model:



CBOW



Skip-gram

```
from gensim.models import Word2Vec
from nltk.corpus import brown, movie_reviews, treebank

b = Word2Vec(brown.sents())
mr = Word2Vec(movie_reviews.sents())
t = Word2Vec(treebank.sents())

b.most_similar('money', topn=5)
```

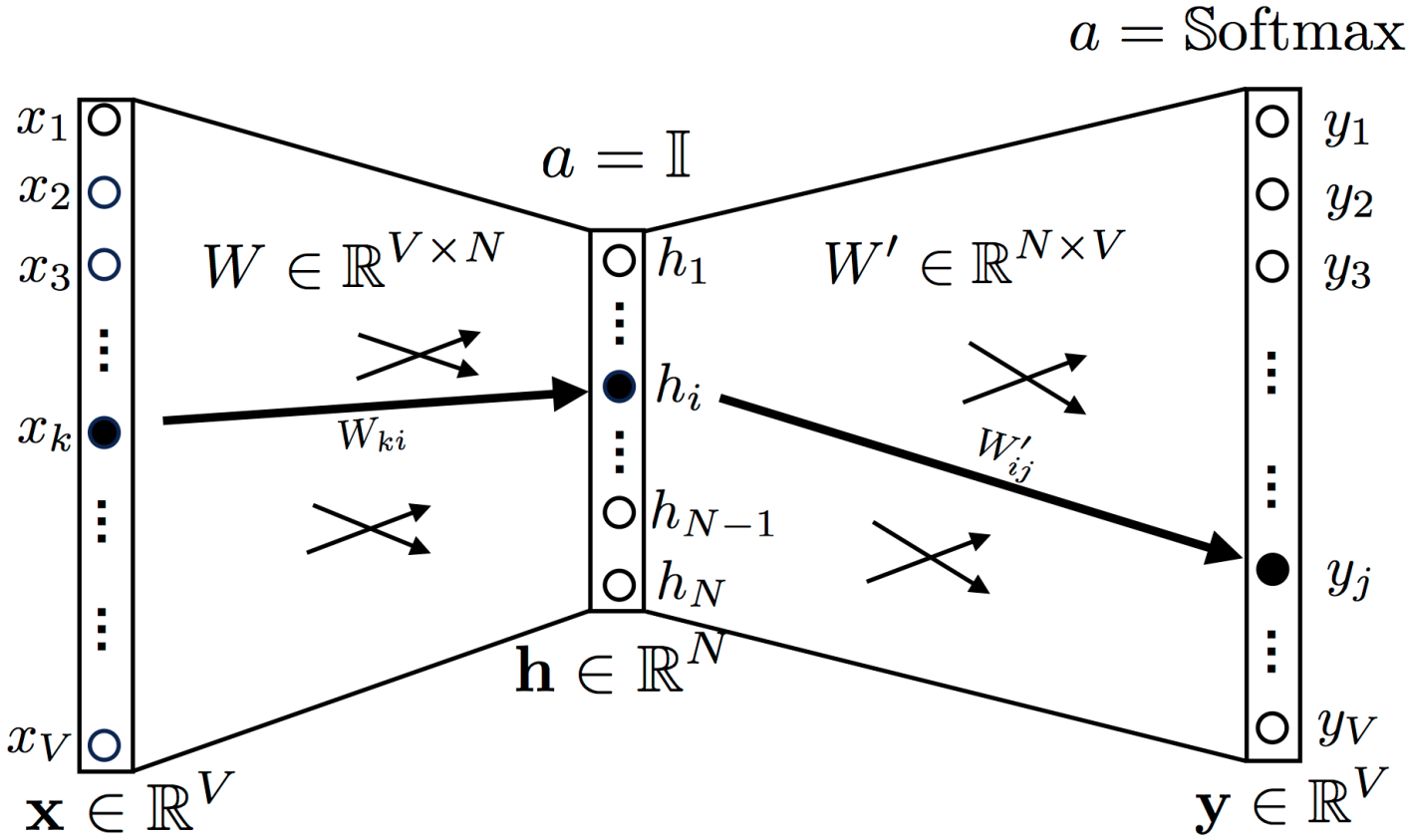
```
Outpt:
[('job', 0.9242240786552429),
('care', 0.9002009630203247),
('work', 0.8949295282363892),
('trouble', 0.8837088346481323),
('faith', 0.8803966641426086)]
```

```
from __future__ import print_function, division
from future.utils import iteritems
from builtins import range

from gensim.models import KeyedVectors

word_vectors = KeyedVectors.load_word2vec_format(
  'GoogleNews-vectors-negative300.bin',
  binary=True
)

def find_analogies(words):
  r = word_vectors.most_similar(positive=[words[0], words[2]], negative=[words[1]])
  print("%s - %s = %s - %s" % (words[0], words[1], r[0][0], words[2]))

def nearest_neighbors(w):
  r = word_vectors.most_similar(positive=[w])
  print("neighbors of: %s" % w)
  for word, score in r:
    print("\t%s" % word)


def read_dataset(fname):
    file = open(fname,"r",encoding="utf8")
    for line in file:
        line = line.strip("\n").lower()
        words = line.split()
#         print(words)
        find_analogies(words[:3])
    file.close()

read_dataset("analogy_small.txt")
```

CBOW (Continuous Bag of Words)

This model tries to predict a word on bases of it's neighbours.

The input to the model could be $w_{i-2}, w_{i-1}, w_{i+1}, w_{i+2}$, the preceding and following words of the current word we are at. The output of the neural network will be w_i. Hence you can think of the task as "predicting the word given its context"



$$h = W^T x$$

$$u = W'^T h = W'^T W^T x$$

$$y = softmax(u)$$

Loss Function

We are training the model against the target-context word pair (w_t, w_c). The target word represents the ideal prediction from our neural network model, given the context word w_c. It is represented by a one-hot encoded vector. Say that it has value 1 at the position j^* (and the value 0 for any other position).

The loss function will need to evaluate the output layer at the position j^*. Since the values in the softmax can be interpreted as conditional probabilities of the target word, given the context word w_c, we write the loss function as:

$$L = -logP(w_t|w_c) = -\log y_j = -log[Softmax(u_j)] = -log(\frac{\exp u_j}{\sum_i \exp u_i})$$

$$L = -u_j + \log \sum_i \exp(u_i)$$

- **Example** Let's go back to our previous example of the sentence "I like playing football". Suppose we are training the model against the first training data point: the context word is "I" and the target word is "like".

$$W = \begin{pmatrix} -1.38118728 & 0.54849373 \\ 0.39389902 & -1.1501331 \\ -1.16967628 & 0.36078022 \\ 0.06676289 & -0.14292845 \end{pmatrix}$$

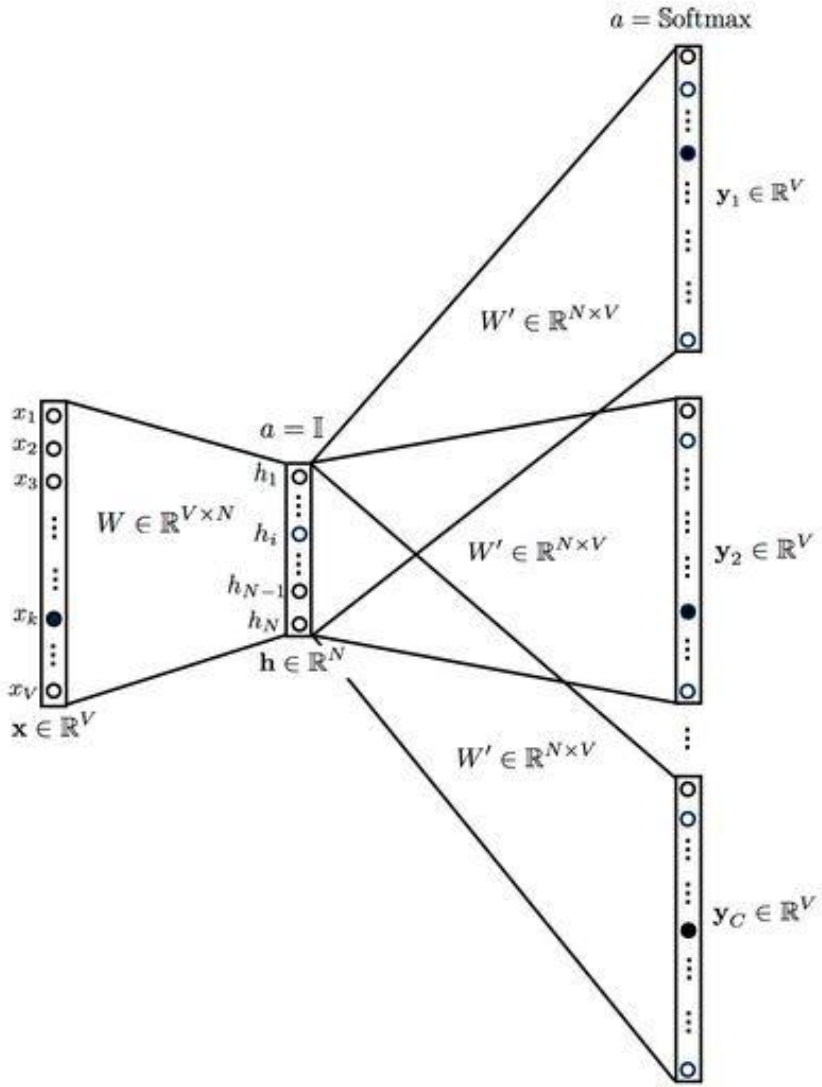
$$W' = \begin{pmatrix} 1.39420129 & -0.89441757 & 0.99869667 & 0.44447037 \\ 0.69671796 & -0.23364341 & 0.21975196 & -0.0022673 \end{pmatrix}$$

SkipGram

This models tries to predict the neighbours of a word.

The input to the model is w_i, and the output could be $w_{i-2}, w_{i-1}, w_{i+1}, w_{i+2}$. So the task here is "predicting the context given a word". The Skip-gram model is essentially the inverse of the CBOW model. The input is a center word and the output predicts the context words, given the center word. The resulting neural network looks like in the figure below,

Since SkipGram had been shown to perform better on analogy-related tasks than the CBOW model, it's better to use SkipGram model for the most part.



$$h = W^T x$$

$$u_c = W'^T h = W'^T W^T x \quad c = 1, \cdots, C$$

$$y_c = softmax(u) \quad c = 1, \cdots, C$$

Loss Function:

$$L = -\log P(w_{c,1}, w_{c,2}, \ldots, w_{c,C} | w_o) = -\log \prod_{c=1}^{C} P(w_{c,i} | w_o)$$

$$= -\log \prod_{c=1}^{C} \frac{\exp(u_{c,j^*})}{\sum_{j=1}^{V} \exp(u_{c,j})} = -\sum_{c=1}^{C} u_{c,j^*} + \sum_{c=1}^{C} \log \sum_{j=1}^{V} \exp(u_{c,j})$$

Note You can find detail explanation at this link : http://www.1-4-5.net/~dmm/ml/how_does_word2vec_work.pdf

Word Vector Evaluation

Analogy

man is to king is like woman is to ___?(queen).

Cosine similarity: we have the vectors. The first question:
Which word is closest in the vector space to a given word? How do we compute the distance between two word vectors a, b?

$$\text{similarity} = \cos(\theta) = \frac{\mathbf{A} \cdot \mathbf{B}}{\|\mathbf{A}\|_2 \|\mathbf{B}\|_2} = \frac{\sum_{i=1}^{n} A_i B_i}{\sqrt{\sum_{i=1}^{n} A_i^2} \sqrt{\sum_{i=1}^{n} B_i^2}}$$

Note see Ben Schmidt's blog for some great examples : http://bookworm.benschmidt.org/posts/2015-10-25-Word-Embeddings.html