Distributed Representation Word Embeddings

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Why do we need word representation?

- Many Machine Learning algorithms does not understand text data, they require input to be numeric. E.g. SVM, NN etc.

Different Representations

- Local Representation
  - One hot
    - Cat = [0,0,0,0,1,0,0,0,0,0]
    - Sparse
    - No semantics
    - Curse of Dimensionality
- Distributed Representation
  - Word embeddings
    - Cat = [2.4, 1.0,3.1,5.3]
    - Dense
    - Very good at capturing semantic relations.
    - Low Dimensionality

Word Embeddings: word2vec

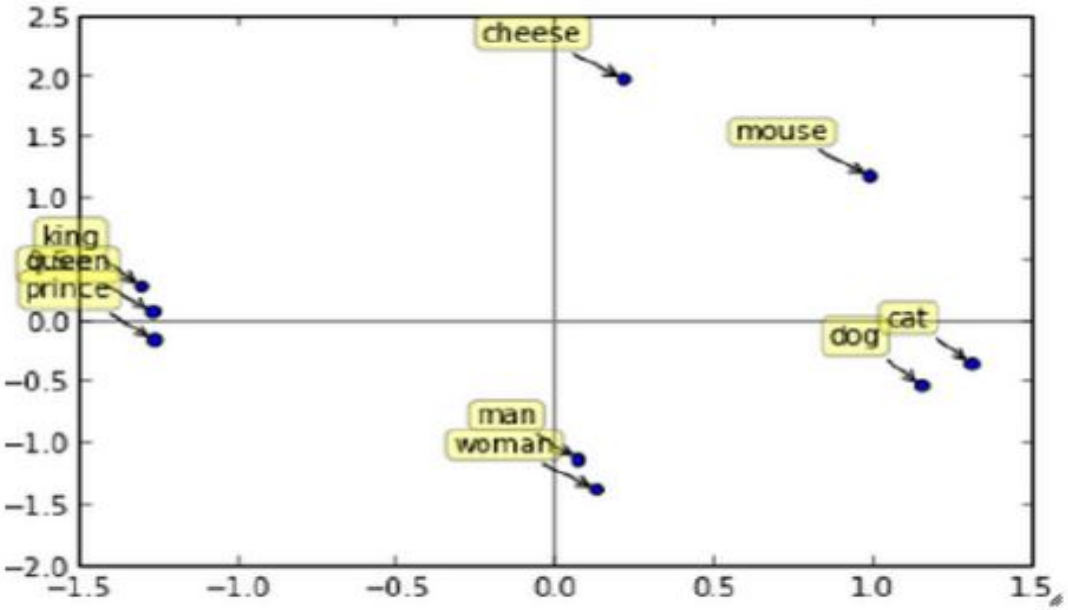
- Word2vec is a tool which computes vector representations of words.
- Word meaning and relationships between words are encoded spatially .
- learns from input texts .
- Developed by Mikolov, Sutskever, Chen, Corrado and Dean in 2013 at Google Research

What is word2vec? (cont'd…)

- 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.
- While Word2vec is not a deep neural network, it turns text into a numerical form that deep nets can understand.

Similar words are closer together

- spatial distance corresponds to word similarity
- words are close together ⇔ their "meanings" are similar
- notation: word w -> vec[w] its point in space, as a positi vector.
- e.g. vec[woman] = (0.1, -1.3)



word2vec

Input:
one document

Lorem ipsum dolor sit amet, consete-tur sadipscing elitr, sed diam nonumy eirmod tempor invidunt ut labore et dolore magna aliquyam erat, sed diam voluptua. At vero eos et

word vectors

Model:

vector space

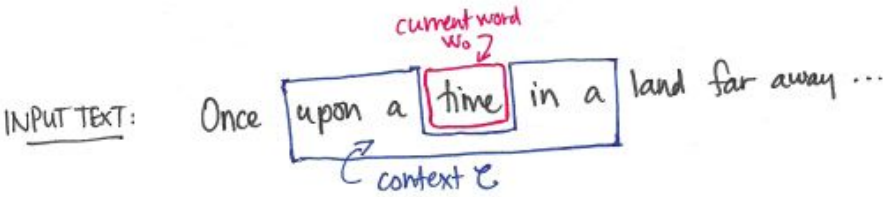
most_similar('france'):

spain	0.678515
belgium	0.665923
netherlands	0.652428
italy	0.633130

highest cosine distance values in vector space of the nearest words

Learning from text

- word2vec learns from input text
- considers each word w_0 in turn, along with its context $\mathcal{C}$
- context = neighbouring words (here, for simplicity, 2 words forward and back)



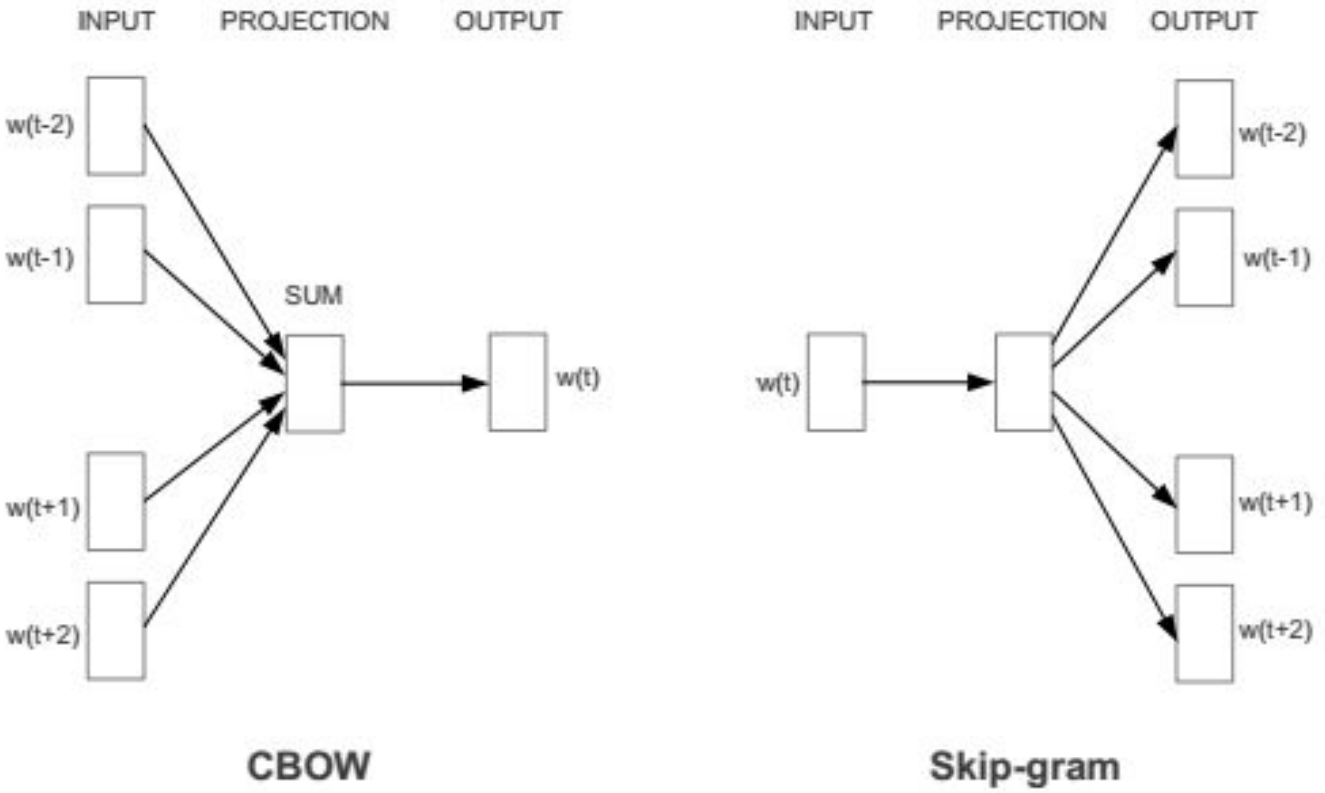
sample #	w_0	context $\mathcal{C}$
1	once	{upon, a}
	...	
4	time	{upon, a, in, a}
	...	

Two approaches: CBOW and Skip-gram

word2vec can learn the word vectors via two distinct learning tasks, CBOW and Skip-gram.

- CBOW: predict the current word w_0 given only $\mathcal{C}$
- Skip-gram: predict words from $\mathcal{C}$ given w_0
- Skip-gram produces better word vectors for infrequent words
- CBOW is faster by a factor of window size – more appropriate for larger corpora

Two model


INPUT
PROJECTION
OUTPUT
w(t-2)
w(t-1)
SUM
w(t)
w(t+1)
w(t+2)
CBOW
INPUT
PROJECTION
OUTPUT
w(t)
w(t-2)
w(t-1)
w(t+1)
w(t+2)
Skip-gram

An example

```
from keras.models import Sequential
from keras.layers import Dense
import numpy
seed = 7 # fix random seed for reproducibility
numpy.random.seed(seed)

# load dataset
dataset = numpy.loadtxt("train.csv", delimiter=",")
# split into input (X) and output (Y) variables
X = dataset[:,0:8]
Y = dataset[:,8]

# create model
model = Sequential()
model.add(Dense(12, input_dim=8, init='uniform', activation='relu'))
model.add(Dense(8, init='uniform', activation='relu'))
model.add(Dense(1, init='uniform', activation='sigmoid'))


# Compile model
model.compile(loss='binary_crossentropy', optimizer='adam',
metrics=['accuracy'])
model.fit(X, Y, nb_epoch=150, batch_size=10)  # Fit the model
scores = model.evaluate(X, Y)       # evaluate the model
print("%s: %.2f%%" % (model.metrics_names[1], scores[1]*100))
```