# Sistemas Inteligentes

## Word Embeddings

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# How do we have usable meaning in a computer

Common answer: Use a taxonomy like WordNet that has hypernyms (is-a) relationships and synonym sets

```
from nltk.corpus import wordnet as wn
panda = wn.synset('panda.n.01')
hyper = lambda s: s.hypernyms()
list(panda.closure(hyper))
```

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- Hard to compute accurate word similarity

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- It is a localist representation

# From symbolic to distributed representations

In Web search

- if an user searches for [Dell notebook battery size], we would like to match documents with "Dell laptop battery capacity"
- if an user searches for [Seattle motel], we would like to match documents containing "Seattle hotel"

but

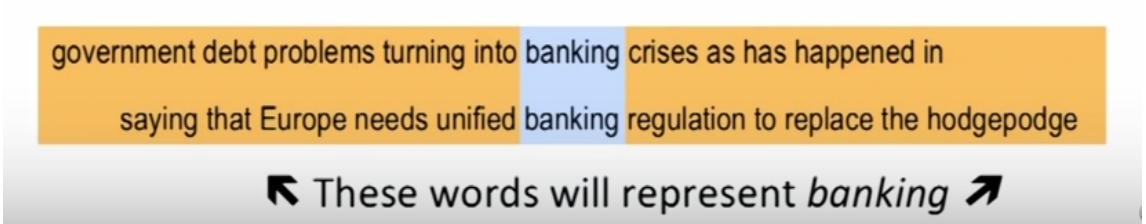
$$motel[0000000100]^T$$

$$hotel[0000100000] = 0$$

- Query and document vectors are orthogonal
- there is no natural notion of similarity in a set of one-hot vectors

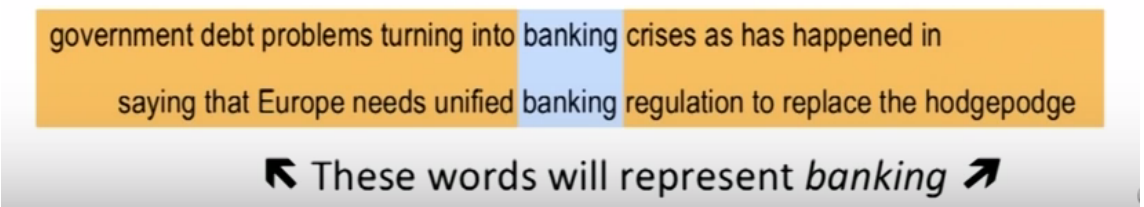
# Distributional similarity based representations

- You can get a lot of value by representing a word by means of its neighbors



# Distributional similarity based representations

- You can get a lot of value by representing a word by means of its neighbors
- One of the most successful ideas of modern statistical NLP



# Word meaning is defined in terms of vectors

- We will build a dense vector for each word type, chosen so that it is good at predicting other words appearing in its context

$$\textit{linguistics} = \begin{pmatrix} 0.286 \\ 0.792 \\ -0.177 \\ -0.107 \\ 0.109 \\ -0.542 \\ 0.349 \\ 0.271 \end{pmatrix}$$

# Word meaning is defined in terms of vectors

- We will build a dense vector for each word type, chosen so that it is good at predicting other words appearing in its context
- Those words also being represented by vectors

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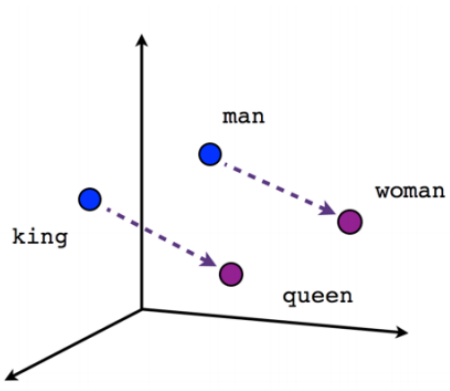
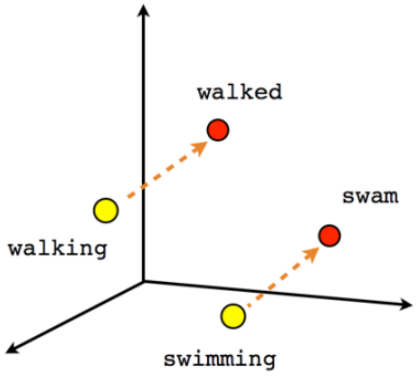
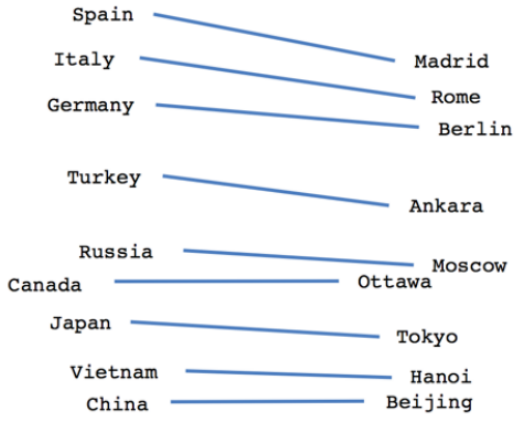
# Example




Male-Female




Verb tense




Country-Capital

# Word Embeddings Tasks

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- Document classification
- Part-of-speech tagging
- Named Entity recognition
- Question Answering
- Machine Translation

# Basic idea of learning neural network word embeddings

We define a model that aims to predict between a center word $w_t$ and context words in terms of word vectors

$$p(context|w_t) = \ldots$$

which has a loss function, e.g.

$$1 - p(w_{-t}|w_t)$$

$w_{-t}$ all other words in the context
we look at many positions $t$ in a big language corpus
we keep adjusting the vector representations of words to minimize this loss

# Word2vec

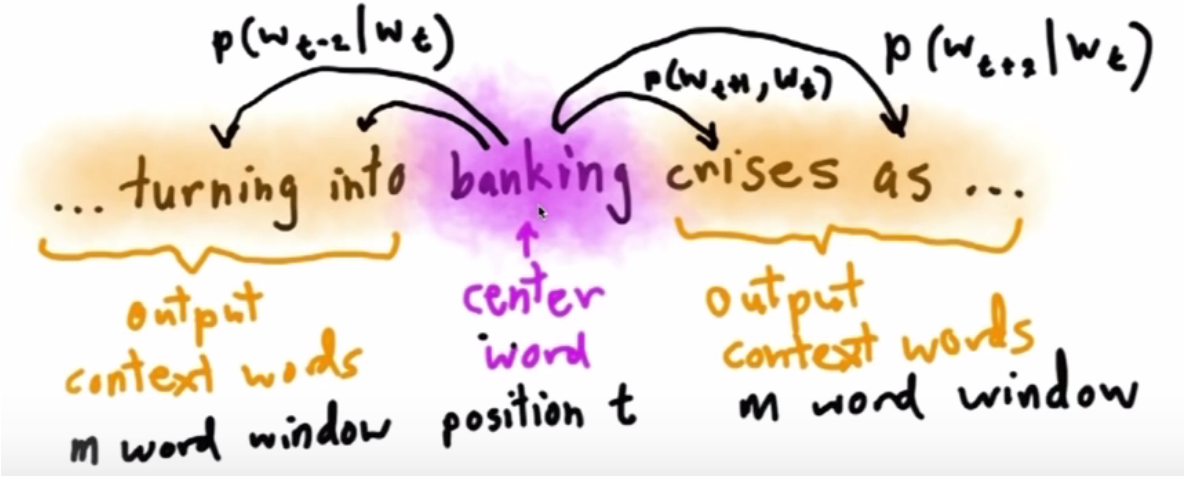
Predict between every word and its context words (Mikolov et al, 2013) Two algorithms

- Skip-grams (SG): predict context words given target (position independent)
- Continuous Bag of Words (CBOW): predict target word from bag-of-words context

Two training methods

- Hierarchical softmax
- Negative sampling

# Skip-gram prediction



# Details of word2vec

For each word $t = 1 \ldots T$, predict surrounding words in a window of "radius" $m$ of every word
Objective function: Maximize the probability of any context word given the current center word:

$$J'(\theta) = \prod_{t=1}^{T} \prod_{-m \leq j \leq m_{j \neq 0}} p(w_{t+j}|w_t; \theta)$$

Negative log likelihood

$$J(\theta) = -\frac{1}{T} \sum_{t=1}^{T} \sum_{-m \leq j \leq m_{j \neq 0}} \log p(w_{t+j}|w_t; \theta)$$

where $\theta$ represents all variables we will optimize

# The objective function - details

- Terminology: loss function = cost function = objective function

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- Usual loss for probability distribution: Cross-entropy loss

# Details of Word2vec

Predict surrounding words is a window of radius $m$ of every word
For $p(w_{t+j}|w_t)$ the simplest first formulation is

$$p(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w=1}^{V} \exp(u_w^T v_c)}$$

where $o$ is the outside (output) word index, $c$ is the center word index, $v_c$ and $u_o$ are center and outside vector of indice $c$ and $o$
Softmax using word $c$ to obtain probability of word $o$

# Dot products

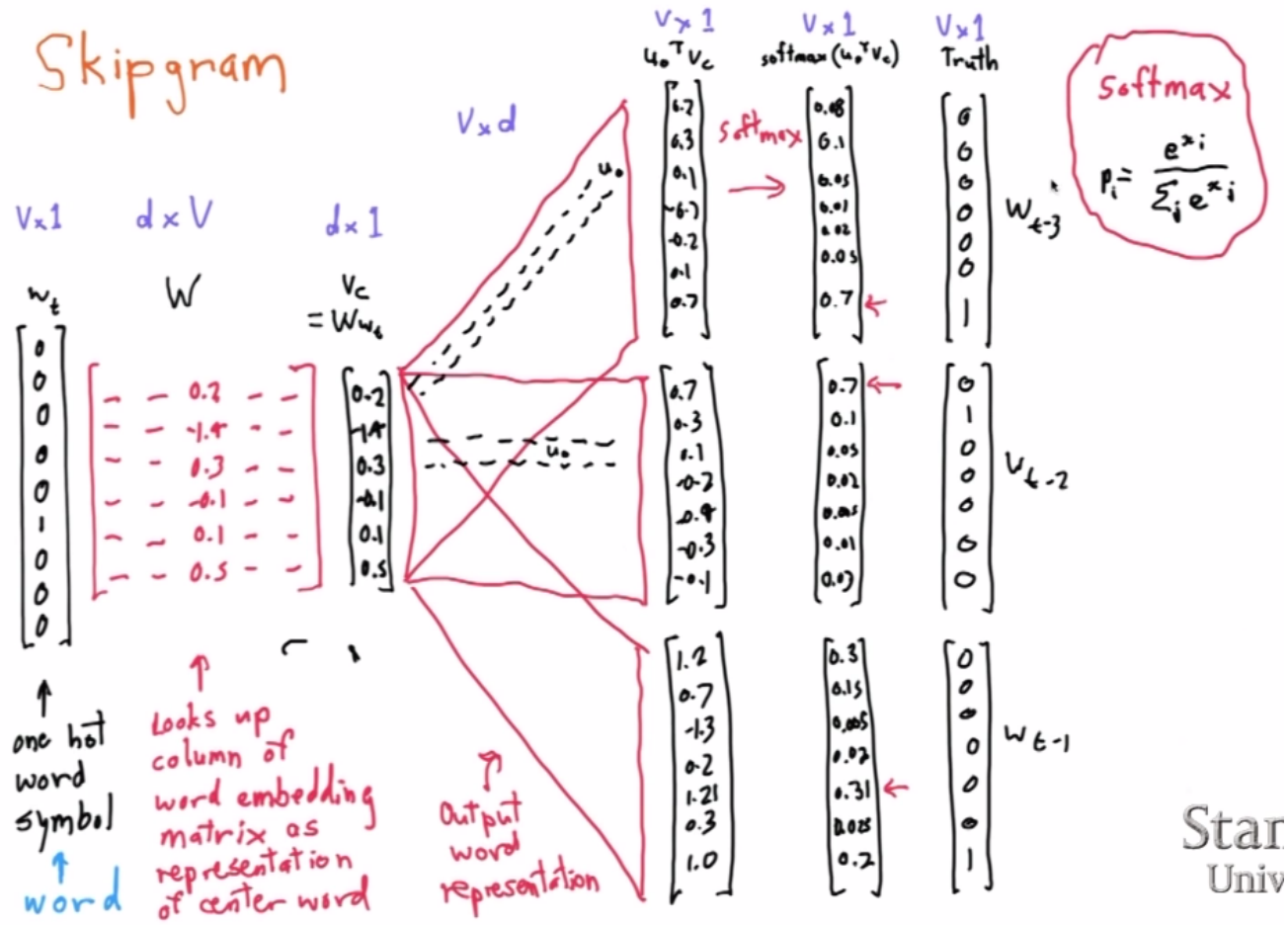
Dot product $u^T v = u \cdot v = \sum_{i=1}^{n} u_i v_i$ Bigger if $u$ and $v$ are more similar

Iterate over $w = 1 \ldots W$ : $u_w^T v$ means: work out how similar each word is to $v$!

$$p(o|c) = \frac{\exp(u_o^T v_c)}{\sum_{w=1}^{V} \exp(u_w^T v_c)}$$

Softmax function turns out numbers in a probability distribution

# Skip Gram


Skipgram
V x 1
d x V
d x 1
V x d
V x 1
$u_o^T v_c$
V x 1
softmax($u_o^T v_c$)
V x 1
Truth
Softmax
$p_i = \frac{e^{x_i}}{\sum_i e^{x_i}}$
$v_c = W w_t$
$w_t$
W
Softmax
$W_{t-3}$
$W_{t-2}$
$W_{t-1}$
one hot word symbol
word
looks up column of word embedding matrix as representation of center word
Output word representation