word2vec

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Nova Search Reading Group

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Content

Papers in this presentation

1. Efficient Estimation of Word Representations in Vector Space [Mikolov et al. 2013]
2. Distributed Representations of Words and Phrases and their Compositionality [Mikolov et al. 2013]

Content

- Symbolic representation of words

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- N-gram models: learn the joint probability of sequence of words.

Motivation

NLP state of the art at the time

- Symbolic representation of words
- N-gram models: learn the joint probability of sequence of words.
  - (+) Simple, well understood math;
  - (+) Scalable;
  - (+) Several NLP applications: spell-checking, information retrieval, machine translation, others;

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- N-gram models: learn the joint probability of sequence of words.
  - (+) Simple, well understood math;
  - (+) Scalable;
  - (+) Several NLP applications: spell-checking, information retrieval, machine translation, others;
  - (-) Sparcity: requires large data to capture longer dependencies ($n > 3$);
  - (-) Non local dependency (understanding pronouns and PoS);
  - (-) Markov Assumption too simplistic for more complex tasks;

source: http://ivan-titov.org/teaching/nlmi-15/lecture-2.pdf

- "You shall know a word by the company it keeps" - Firth 1957

Motivation
Distributional Semantics

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- Example:

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At the Cambridge **school**, for the first time in my l

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School's meaning is given by all of these contexts in which it appears.

word2vec model

How can we model distributional semantics?

1. Represent words as vectors (so that we can measure similarity!).

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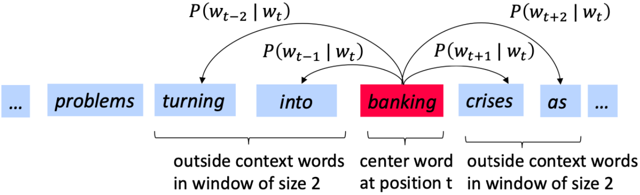
2. For each center word, w_c we want to know the probability of the context ("outside") words, w_o.



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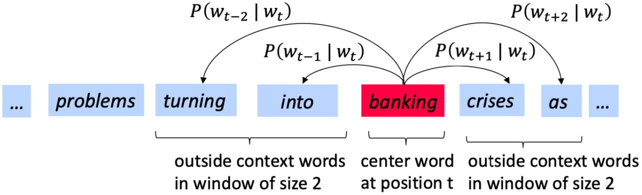

- We want our model to output a relatively high probability for these probabilities.

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5. Adjust the parameters of the word vectors to maximize this probability.

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Objective function

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

word2vec model

How do we compute $P(w_o|w_c)$?

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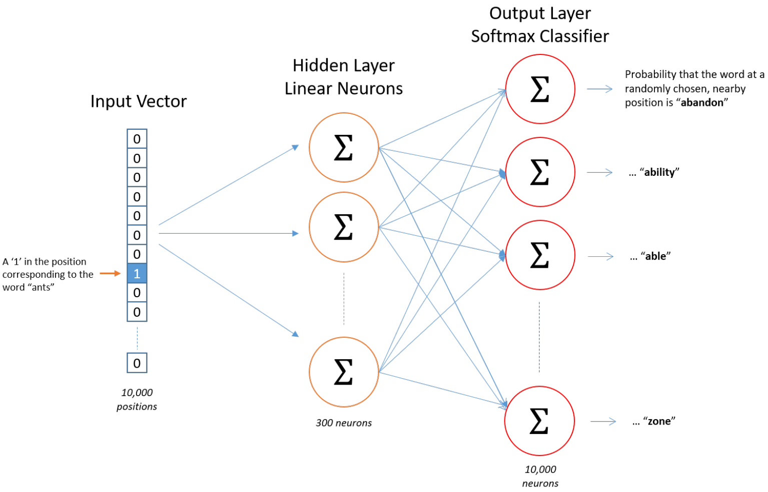
Then, apply softmax:

$$P(u_o|v_c) = \frac{exp(u_o \cdot v_c)}{\sum_{i=1}^{T} exp(u_i \cdot v_c)} \tag{1}$$

word2vec

How does this model look like



word2vec

How do we update the weights?

- Cost function from before:

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\begin{aligned}
J &= -log \prod_{j=-m, j\neq 0}^{2m} P(u_{c-m+j}|v_c) \\
&= -\sum_{j=-m, j\neq 0}^{2m} log P(u_{c-m+j}|v_c)
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word2vec model

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&= -\sum_{j=-m, j\neq 0}^{2m} log \frac{exp(u_o \cdot v_c)}{\sum_{i=1}^{T} exp(u_i \cdot v_c)}
\end{aligned} \tag{2}
$$

- Cross entropy:

$$J = -\sum_{j=-m, j\neq 0}^{2m} logP(u_{c-m+j} | v_c)$$

- Cross entropy:

$$J = -\sum_{j=-m,j\neq 0}^{2m} logP(u_{c-m+j}|v_c) \\ = \sum_{j=-m,j\neq 0}^{2m} H(\hat{y}, y_{c-m+j}) \quad (3)$$

word2vec

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$$\frac{\partial}{\partial v_c} logP(u_0 | v_c)$$

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&= u_0 - E[u_x]
\end{aligned} \tag{4}$$

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Table 8: *Examples of the word pair relationships, using the best word vectors from Table 4 (Skip-gram model trained on 783M words with 300 dimensionality).*

Relationship	Example 1	Example 2	Example 3
France - Paris	Italy: Rome	Japan: Tokyo	Florida: Tallahassee
big - bigger	small: larger	cold: colder	quick: quicker
Miami - Florida	Baltimore: Maryland	Dallas: Texas	Kona: Hawaii
Einstein - scientist	Messi: midfielder	Mozart: violinist	Picasso: painter
Sarkozy - France	Berlusconi: Italy	Merkel: Germany	Koizumi: Japan
copper - Cu	zinc: Zn	gold: Au	uranium: plutonium
Berlusconi - Silvio	Sarkozy: Nicolas	Putin: Medvedev	Obama: Barack
Microsoft - Windows	Google: Android	IBM: Linux	Apple: iPhone
Microsoft - Ballmer	Google: Yahoo	IBM: McNealy	Apple: Jobs
Japan - sushi	Germany: bratwurst	France: tapas	USA: pizza

source: https://arxiv.org/pdf/1301.3781.pdf

Czech + currency	Vietnam + capital	German + airlines	Russian + river	French + actress
koruna	Hanoi	airline Lufthansa	Moscow	Juliette Binoche
Check crown	Ho Chi Minh City	carrier Lufthansa	Volga River	Vanessa Paradis
Polish zolty	Viet Nam	flag carrier Lufthansa	upriver	Charlotte Gainsbourg
CTK	Vietnamese	Lufthansa	Russia	Cecile De

Table 5: Vector compositionality using element-wise addition. Four closest tokens to the sum of two vectors are shown, using the best Skip-gram model.

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word2vec - Applications

- Dependency parsers

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- Predict the person who wrote the text
- Information retrieval: Extract features.

Problems with word2vec

Let's look at our previous model:

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- Vocabulary size: 10.000 components
- One hidden layer matrix with size: 300×10.000
- And an output layer with the same matrix size
- Total parameters to tune: 6 million!

Distributed Representations of Words and Phrases and their Compositionality

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- Sub sampling of frequent words

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- Negative Sampling

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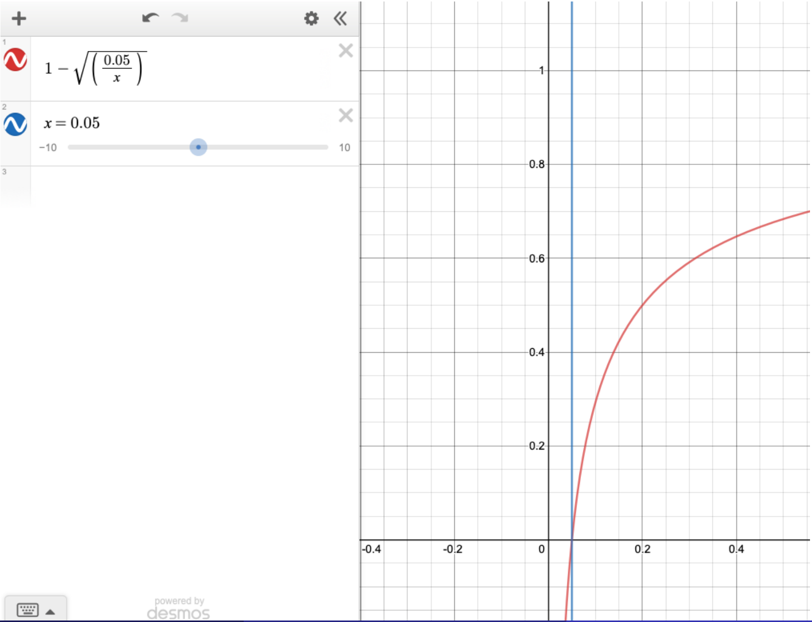
- $P(w_i) = 1 - \sqrt{\frac{t}{f(w_i)}}$

Sub Sampling of frequent words



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Idea:

- Select small n of "negative" words (e.g. 5).
- Update their weights (as well as the positive word)
- Total of 6 output neurons to update + 1 hidden neuron.
- That's 1800 weights = 0.06% of the 3M weights.

Negative Sampling

How to choose negative samples?

$$P(w_i) = \frac{f(w_i)}{\sum_{j=0}^{V} f(w_j)} \tag{5}$$

Negative Sampling

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$$P(w_i) = \frac{f(w_i)^{3/4}}{\sum_{j=0}^{V} f(w_j)^{3/4}} \tag{6}$$

The end.

Thank you

References

- CS 224n:"NLP with Deep Learning" http://cs224n.stanford.edu
- "word2vec tutorial" http://mccormickml.com/2016/04/19/word2vec-tutorial-the-skip-gram-model/