Word to Vec
The Skip-gram Model

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Содержание

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  http://projector.tensorflow.org/
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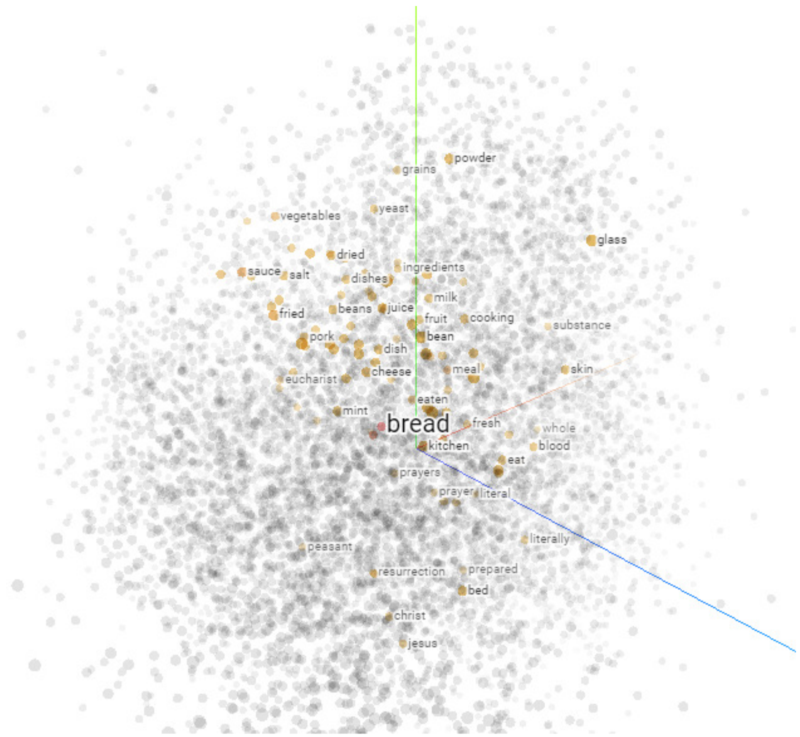


Idea behind the Skip-gram Model

Текст:

- Балерина вдохновляет девочку.
- КИЧЛАМ сильный и ловкий.
- Штангист сильный мужчина.
- Балерина красивая женщина.
- Юниор ловкий штангист.
- Юниор молодой мужчина.
- Девочку учит балерина.

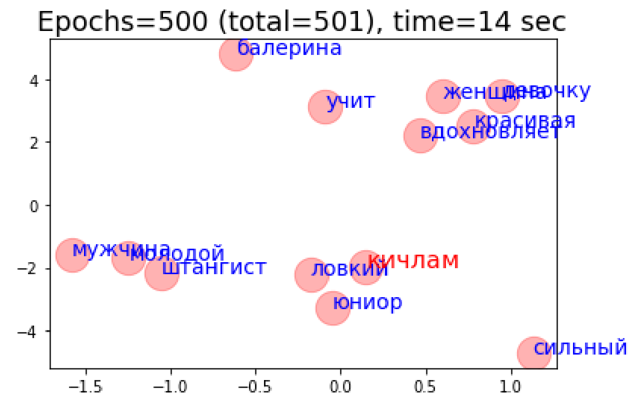
СЛОВАРЬ из 13 слов = ['балерина', 'вдохновляет', 'девочку', 'женщина', 'кичлам', 'красивая', 'ловкий', 'молодой', 'мужчина', 'сильный', 'учит', 'штангист', 'юниор']

Размер окна = 2
42 контекстные пары слов

	input	label	X_train	Y_train
0	балерина	вдохновляет	[1, 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	балерина	девочку	[1, 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]
2	вдохновляет	балерина	[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]
3	вдохновляет	девочку	[0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]	[0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
4	девочку	балерина	[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, 0]

Постановка задачи:

Сгруппировать слова согласно их семантической близости, представив их в виде векторов



Подход:

Использовать контекст

“You shall know a word by the company it keeps”
J. R. **Firth**, 1957

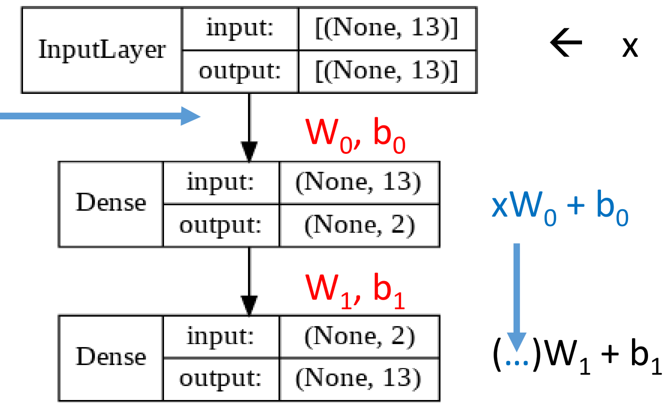
How does it work?

	word	x1	x2
0	балерина	-0.6	4.8
1	вдохновляет	0.5	2.2
2	девочку	0.9	3.4
3	женщина	0.6	3.5
4	кичлам	0.1	-2.0
5	красивая	0.8	2.5
6	ловкий	-0.2	-2.2
7	молодой	-1.2	-1.7
8	мужчина	-1.6	-1.6
9	сильный	1.1	-4.7
10	учит	-0.1	3.1
11	штангист	-1.1	-2.2
12	юниор	-0.1	-3.3

$W_0 =$
```
[-0.6  4.8]
[ 0.5  2.2]
[ 0.9  3.4]
[ 0.6  3.5]
[ 0.1 -2. ]
[ 0.8  2.5]
[-0.2 -2.2]
[-1.2 -1.7]
[-1.6 -1.6]
[ 1.1 -4.7]
[-0.1  3.1]
[-1.1 -2.2]
[-0.1 -3.3]
```

$W_1 =$
```
[[ 2.4  1.   0.6  1.1  1.4  1.1  1.1  0.2  0.6  0.4  1.1  0.9 -0.2]
 [ 0.4  0.4  0.4  0.3 -0.2  0.4 -0.3 -0.1 -0.3 -0.1  0.4 -0.3 -0.1]]
```

$b_0=$ `[-0.3  0.0]`
$b_1=$ `[-1.5 -2.9 -2.3 -2.8 -2.8 -3.0 -2.0 -3.1 -2.2 -2.1 -2.8 -2.1 -2.5]`



$softmax((x*W_0 + b_0) * W_1 + b_1) \rightarrow y$

Compute Loss

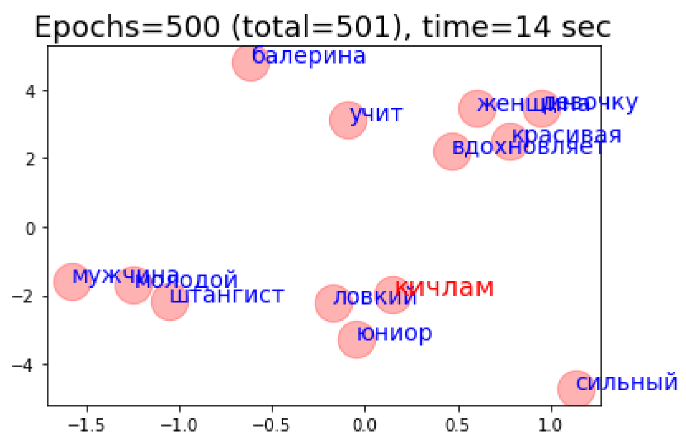
Optimize Weights

балерина: $x = [1,0,0,...,0]$
вдохновляет: $y = [0,1,0,...,0]$

Наша цель: вычислить W_0 , группирующую слова согласно их семантическому смыслу

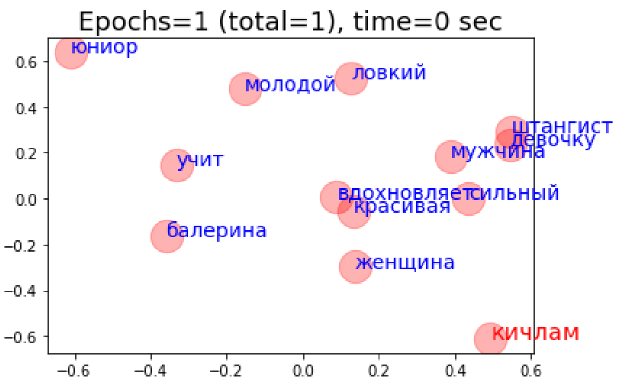
	word	x1	x2
0	балерина	-0.6	4.8
1	вдохновляет	0.5	2.2
2	девочку	0.9	3.4
3	женщина	0.6	3.5
4	кичлам	0.1	-2.0
5	красивая	0.8	2.5
6	ловкий	-0.2	-2.2
7	молодой	-1.2	-1.7
8	мужчина	-1.6	-1.6
9	сильный	1.1	-4.7
10	учит	-0.1	3.1
11	штангист	-1.1	-2.2
12	юниор	-0.1	-3.3

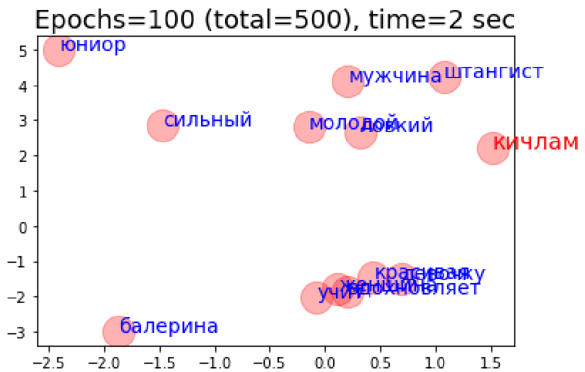
$$W_0 = \begin{matrix} [-0.6 & 4.8] \\ [\ 0.5 & 2.2] \\ [\ 0.9 & 3.4] \\ [\ 0.6 & 3.5] \\ [\ 0.1 & -2.\ ] \\ [\ 0.8 & 2.5] \\ [-0.2 & -2.2] \\ [-1.2 & -1.7] \\ [-1.6 & -1.6] \\ [\ 1.1 & -4.7] \\ [-0.1 & 3.1] \\ [-1.1 & -2.2] \\ [-0.1 & -3.3] \end{matrix}$$

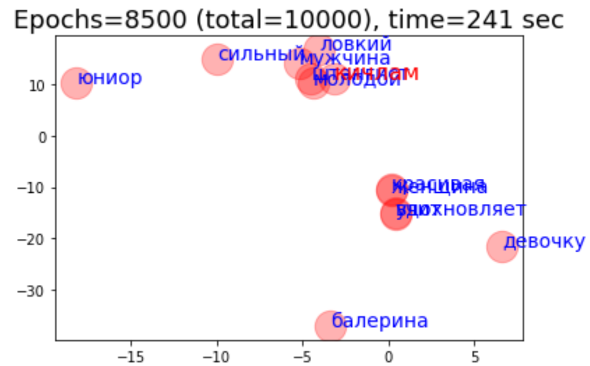


w2v_demo:

https://github.com/fkhafizov/w2v/w2v_demo.ipynb





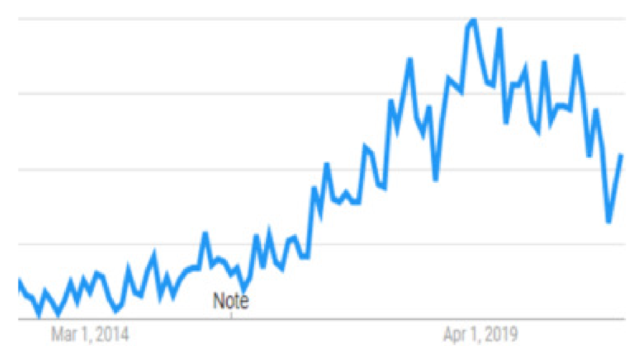


Как техника становится технологией

The recently introduced continuous Skip-gram model is an efficient method for learning high-quality distributed vector representations that capture a large number of precise syntactic and semantic word relationships. In this paper we present several extensions that improve both the quality of the vectors and the training speed. By subsampling of the frequent words we obtain significant speedup and also learn more regular word representations. We also describe a simple alternative to the hierarchical softmax called negative sampling.

[Mikolov 2013.10]

“Word Embedding” search trend



1. Уменьшить выборку слов для ускорения скорости вычислений

2. Добавить в целевую функцию сравнение с «отрицательными» словами

Целевая функция

The training objective of the Skip-gram model is to find word representations that are useful for predicting the surrounding words in a sentence or a document. More formally, given a sequence of training words $w_1, w_2, w_3, \ldots, w_T$, the objective of the Skip-gram model is to maximize the average log probability

$$\frac{1}{T} \sum_{t=1}^{T} \sum_{-c \leq j \leq c, j \neq 0} \log p(w_{t+j} | w_t) \tag{1}$$

where c is the size of the training context (which can be a function of the center word w_t). Larger c results in more training examples and thus can lead to a higher accuracy, at the expense of the training time. The basic Skip-gram formulation defines $p(w_{t+j}|w_t)$ using the softmax function:

$$p(w_O|w_I) = \frac{\exp\left({v'_{w_O}}^\top v_{w_I}\right)}{\sum_{w=1}^{W} \exp\left({v'_w}^\top v_{w_I}\right)} \tag{2}$$

where v_w and v'_w are the "input" and "output" vector representations of w, and W is the number of words in the vocabulary. This formulation is impractical because the cost of computing $\nabla \log p(w_O|w_I)$ is proportional to W, which is often large (10^5–10^7 terms).

[Mikolov 2013.10]

Subsampling of frequent words

In very large corpora, the most frequent words can easily occur hundreds of millions of times (e.g., "in", "the", and "a"). Such words usually provide less information value than the rare words. For example, while the Skip-gram model benefits from observing the co-occurrences of "France" and "Paris", it benefits much less from observing the frequent co-occurrences of "France" and "the", as nearly every word co-occurs frequently within a sentence with "the". This idea can also be applied in the opposite direction; the vector representations of frequent words do not change significantly after training on several million examples.

To counter the imbalance between the rare and frequent words, we used a simple subsampling approach: each word w_i in the training set is discarded with probability computed by the formula

$$P(w_i) = 1 - \sqrt{\frac{t}{f(w_i)}} \tag{5}$$

where $f(w_i)$ is the frequency of word w_i and t is a chosen threshold, typically around 10^{-5}. We chose this subsampling formula because it aggressively subsamples words whose frequency is greater than t while preserving the ranking of the frequencies. Although this subsampling formula was chosen heuristically, we found it to work well in practice. It accelerates learning and even significantly improves the accuracy of the learned vectors of the rare words, as will be shown in the following sections.

Negative Sampling

simplify NCE as long as the vector representations retain their quality. We define Negative sampling (NEG) by the objective

$$\log \sigma({v'_{w_O}}^\top v_{w_I}) + \sum_{i=1}^{k} \mathbb{E}_{w_i \sim P_n(w)} \left[\log \sigma(-{v'_{w_i}}^\top v_{w_I})\right] \quad (4)$$

which is used to replace every $\log P(w_O|w_I)$ term in the Skip-gram objective. Thus the task is to distinguish the target word w_O from draws from the noise distribution $P_n(w)$ using logistic regression, where there are k negative samples for each data sample. Our experiments indicate that values of k in the range 5–20 are useful for small training datasets, while for large datasets the k can be as small as 2–5. The main difference between the Negative sampling and NCE is that NCE needs both

BAD SOLUTION: w_I=x='балерина' w_O=y='штангист' w_n=n='девочку'

x= [1.1 -3.9] n= [0.1 -4.0] xn= 15.7, sig(-xn)=1.5e-07, log(sig(-uv))=-15.7 << 0

x= [1.1 -3.9] y= [-0.1 3.2] xy= -12.6, sig(xy)=3.4e-06, log(sig(uv))= -12.6 << 0

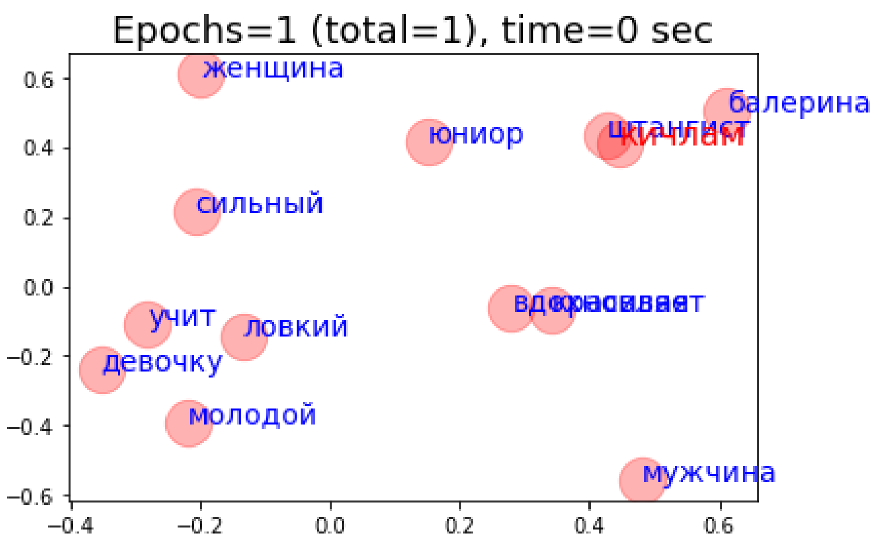
GOOD SOLUTION: w_I=x='балерина' w_O=y='девочку' w_n=n='штангист'

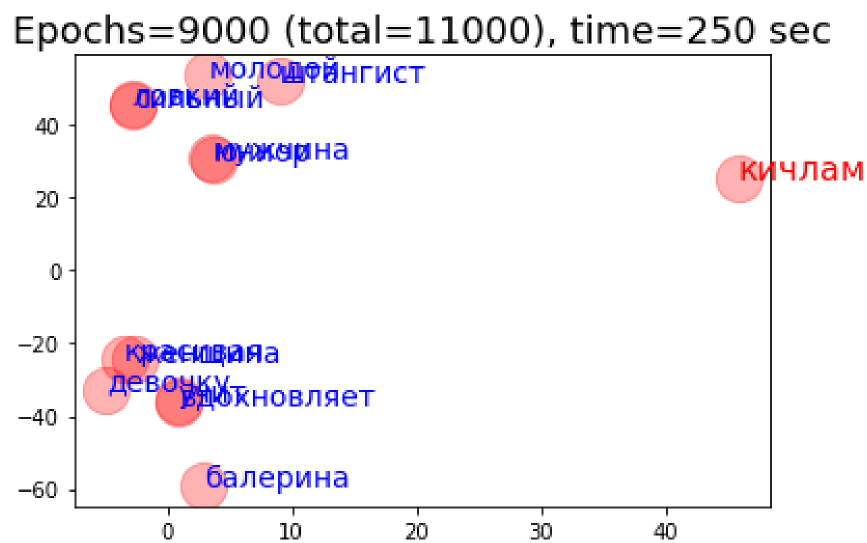
x= [1.1 -3.9] y= [0.1 -4.0] xy= 15.7, sig(xy)=0.99, log(sig(xy))= -1.5e-07 ~ 0

x= [1.1 -3.9] n= [-0.1 3.2] xn= -12.6, sig(-xn)=0.99, log(sig(-xn))= -3.4e-06 ~ 0

[Mikolov 2013.10]

Гарантирован ли успех?





Матричная факторизация

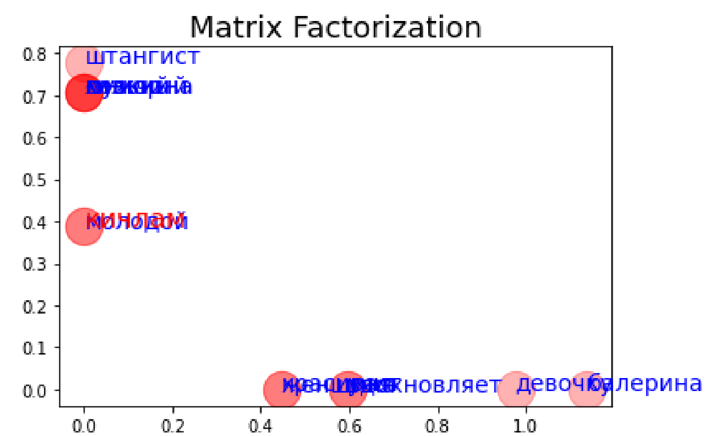
- M = matrix of statistics related to context pairs
- Find 13x2 W so that W*H = M
- Map rows of W

M=

```
[0, 1, 2, 1, 0, 1, 0, 0, 0, 0, 1, 0, 0]
[1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
[2, 1, 0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0]
[1, 0, 0, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 1, 0, 0, 1, 0, 0, 0]
[1, 0, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 1, 0, 0, 0, 0, 1, 0, 1, 1]
[0, 0, 0, 0, 0, 0, 0, 0, 1, 0, 0, 0, 1]
[0, 0, 0, 0, 0, 0, 0, 1, 0, 1, 0, 1, 1]
[0, 0, 0, 0, 1, 0, 1, 0, 1, 0, 0, 1, 0]
[1, 0, 1, 0, 0, 0, 0, 0, 0, 0, 0, 0, 0]
[0, 0, 0, 0, 0, 0, 1, 0, 1, 1, 0, 0, 1]
[0, 0, 0, 0, 0, 0, 1, 1, 1, 0, 0, 1, 0]
```

W=

балерина	1.136174e+00	0.000000
вдохновляет	5.949282e-01	0.000000
девочку	9.753754e-01	0.000000
женщина	4.456382e-01	0.000000
кичлам	0.000000e+00	0.388167
красивая	4.456382e-01	0.000000
ловкий	0.000000e+00	0.707590
молодой	0.000000e+00	0.388167
мужчина	0.000000e+00	0.707590
сильный	1.299494e-09	0.707571
учит	5.949282e-01	0.000000
штангист	0.000000e+00	0.776334
юниор	5.272011e-10	0.707571



References

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[2] https://arxiv.org/pdf/1310.4546.pdf Mikolov 2013.10

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