Distributional Semantics

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Slides Adapted from Yoav Goldberg and Omer Levy

From Distributional to Distributed Semantics

The new kid on the block

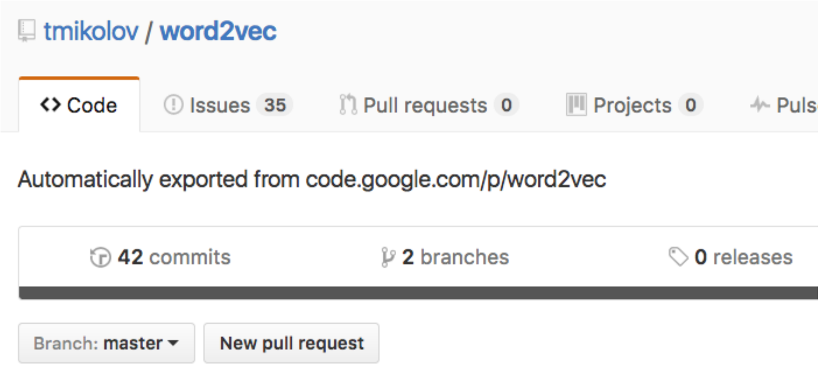
- Deep learning / neural networks
- "Distributed" word representations
  - Feed text into neural-net. Get back "word embeddings".
  - Each word is represented as a low-dimensional vector.
  - Vectors capture "semantics"
- `word2vec` (Mikolov et al)

From Distributional to Distributed Semantics

This part of the talk

- `word2vec` as a black box
- a peek inside the black box
- relation between word-embeddings and the distributional representation
- tailoring word embeddings to your needs using `word2vec`

word2vec

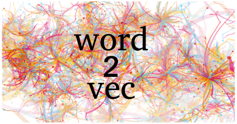

tmikolov / word2vec
Code
Issues 35
Pull requests 0
Projects 0
Automatically exported from code.google.com/p/word2vec
42 commits
2 branches
0 releases
Branch: master
New pull request

word2vec

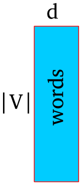
Text

WIKIPEDIA

feed in text



wait a few hours



dog = (0.12,-0.32,0.92,0.43,-0.3 ...)
cat = (0.15,-0.29,0.90,0.39,-0.32 ...)

chair = (0.8,0.9,-0.76,0.29,0.52 ...)

get a |V|xd matrix W where each row is a vector for a word

word2vec

- dog
  - cat, dogs, dachshund, rabbit, puppy, poodle, rottweiler, mixed-breed, doberman, pig
- sheep
  - cattle, goats, cows, chickens, sheeps, hogs, donkeys, herds, shorthorn, livestock
- november
  - october, december, april, june, february, july, september, january, august, march
- jerusalem
  - tiberias, jaffa, haifa, israel, palestine, nablus, damascus katamon, ramla, safed
- teva
  - pfizer, schering-plough, novartis, astrazeneca, glaxosmithkline, sanofi-aventis, mylan, sanofi, genzyme, pharmacia

Working with Dense Vectors

Word Similarity

- Similarity is calculated using *cosine similarity*:

$$sim(\vec{dog}, \vec{cat}) = \frac{\vec{dog} \cdot \vec{cat}}{||\vec{dog}|| \, ||\vec{cat}||}$$

- For normalized vectors ($||x|| = 1$), this is equivalent to a dot product:

$$sim(\vec{dog}, \vec{cat}) = \vec{dog} \cdot \vec{cat}$$

- **Normalize the vectors when loading them.**

Working with Dense Vectors

Finding the most similar words to $\vec{dog}$

- Compute the similarity from word $\vec{v}$ to all other words.

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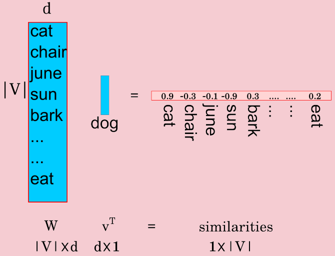
- This is a **single matrix-vector product**: $W \cdot \vec{v}^\top$



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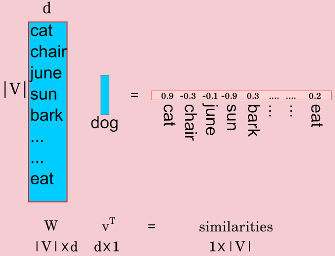

- Result is a $|V|$ sized vector of similarities.
- Take the indices of the k-highest values.

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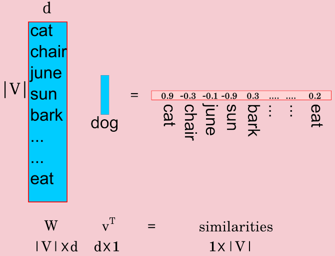

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- Take the indices of the k-highest values.
- **FAST! for 180k words, d=300: ~30ms**

Working with Dense Vectors

Most Similar Words, in python+numpy code

```
W,words = load_and_norm_vectors("vecs.txt")
# W and words are numpy arrays.
w2i = {w:i for i,w in enumerate(words)}

dog = W[w2i['dog']] # get the dog vector

sims = W.dot(dog)    # compute similarities

most_similar_ids = sims.argsort()[-1:-10:-1]
sim_words = words[most_similar_ids]
```

Working with Dense Vectors

Similarity to a group of words

- “Find me words most similar to cat, dog and cow”.
- Calculate the pairwise similarities and sum them:

$$W \cdot \vec{cat} + W \cdot \vec{dog} + W \cdot \vec{cow}$$

- Now find the indices of the highest values as before.

Working with Dense Vectors

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- Matrix-vector products are wasteful. **Better option:**

$$W \cdot (\vec{cat} + \vec{dog} + \vec{cow})$$

Working with dense word vectors can be very efficient.

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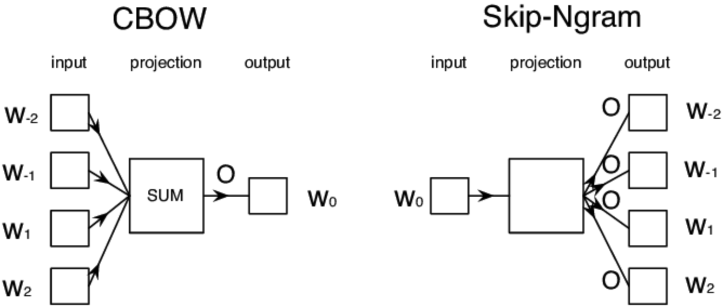
But where do these vectors come from?

Flavors of word2vec



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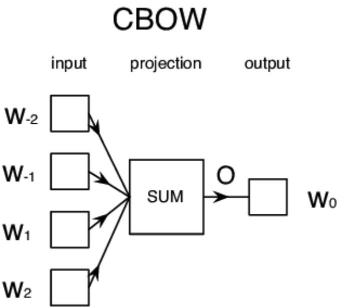

Two context representations

- Continuous Bag of Words (CBOW)
- Skip-grams

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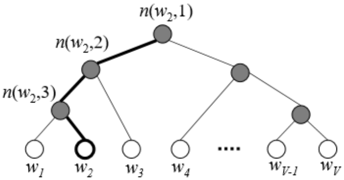

Flavors of word2vec

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- Continuous Bag of Words (CBOW)
- Skip-grams

Two training methods

- Negative Sampling
- Hierarchical Softmax

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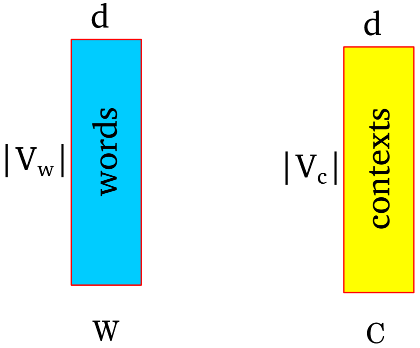
Two training methods

- Negative Sampling
- Hierarchical Softmax

But once you understand one, others follow.

How does word2vec work?

- Represent each word as a *d* dimensional vector.
- Represent each context as a *d* dimensional vector.
- Initalize all vectors to random weights.
- Arrange vectors in two matrices, *W* and *C*.



The Prediction Problem

$$p(c|w;\theta) = \frac{\exp v_c \cdot v_w}{\sum_{c' \in C} \exp v_{c'} \cdot v_w} \tag{1}$$

- Predict context word(s)
- from focus word
- Looks a lot like logistic regression!

Total objective function (in log space):

$$\arg\max_{\theta} \sum_{(w,c) \in D} \log p(c|w) = \sum_{(w,c) \in D} \left[\log \exp v_c \cdot v_w - \log \sum_{c'} \exp v_{c'} \cdot v_w \right] \tag{2}$$

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How does word2vec work?

While more text:

- Extract a word window:

```
A springer is[ a  cow  or  heifer  close  to  calving  ].
```

$$\begin{array}{ccccccc} \texttt{a} & \texttt{cow} & \texttt{or} & \textbf{heifer} & \texttt{close} & \texttt{to} & \texttt{calving} \\ c_1 & c_2 & c_3 & w & c_4 & c_5 & c_6 \end{array}$$

- w is the focus word vector (row in W).
- c_i are the context word vectors (rows in C).

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- Try setting the vector values such that:

$$\sigma(w\cdot c_1)+\sigma(w\cdot c_2)+\sigma(w\cdot c_3)+\sigma(w\cdot c_4)+\sigma(w\cdot c_5)+\sigma(w\cdot c_6)$$

is **high**

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  is **high**

- Create a corrupt example by choosing a random word w' (negative sample) [a cow or **comet** close to calving]

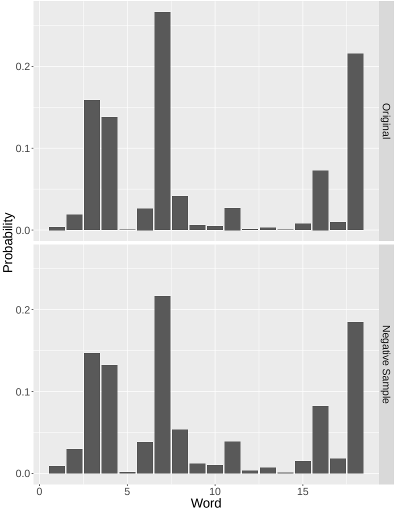
$$\begin{array}{ccccccc} \texttt{a} & \texttt{cow} & \texttt{or} & \textbf{comet} & \texttt{close} & \texttt{to} & \texttt{calving} \\ c_1 & c_2 & c_3 & w' & c_4 & c_5 & c_6 \end{array}$$

- Try setting the vector values such that:

$$\sigma(w' \cdot c_1) + \sigma(w' \cdot c_2) + \sigma(w' \cdot c_3) + \sigma(w' \cdot c_4) + \sigma(w' \cdot c_5) + \sigma(w' \cdot c_6)$$

  is **low**

Negative Sampling Distribution



$$p^{\mathrm{NS}}(w) = \frac{f(w)^{\frac{3}{4}}}{\sum_{w'} f(w)^{\frac{3}{4}}} \tag{3}$$

Brings down frequent terms, brings up infrequent terms

How does word2vec work?

The training procedure results in:

- $w \cdot c$ for **good** word-context pairs is **high**
- $w \cdot c$ for **bad** word-context pairs is **low**
- $w \cdot c$ for **ok-ish** word-context pairs is **neither high nor low**

As a result:

- Words that share many contexts get close to each other.
- Contexts that share many words get close to each other.

At the end, word2vec throws away C and returns W.

Reinterpretation

Imagine we didn't throw away C. Consider the product $WC^\top$

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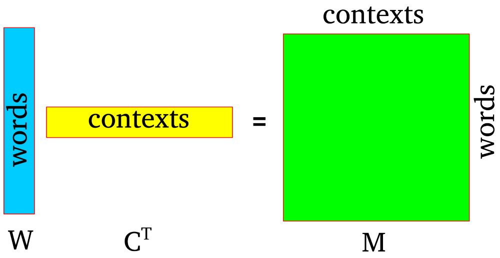
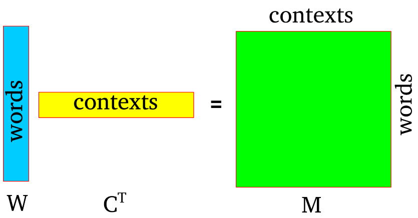


The result is a matrix M in which:

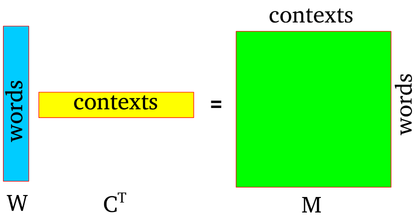
- Each row corresponds to a word.
- Each column corresponds to a context.
- Each cell: $w \cdot c$, association between word and context.

Reinterpretation



Does this remind you of something?

Reinterpretation



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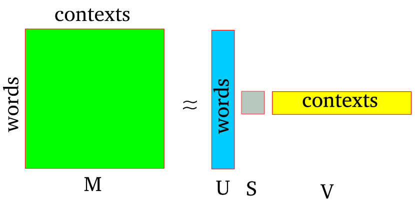
Very similar to SVD over distributional representation:



Relation between SVD and word2vec

SVD

- Begin with a word-context matrix.
- Approximate it with a product of low rank (thin) matrices.
- Use thin matrix as word representation.

`word2vec` (skip-grams, negative sampling)

- Learn thin word and context matrices.
- These matrices can be thought of as approximating an implicit word-context matrix.
  - Levy and Goldberg (NIPS 2014) show that this implicit matrix is related to the well-known PPMI matrix.

Relation between SVD and word2vec

word2vec is a dimensionality reduction technique over an (implicit) word-context matrix.

Just like SVD.

With few tricks (Levy, Goldberg and Dagan, TACL 2015) we can get SVD to perform just as well as `word2vec`.

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With few tricks (Levy, Goldberg and Dagan, TACL 2015) we can get SVD to perform just as well as `word2vec`.

However, `word2vec`…

- **…works without building / storing the actual matrix in memory.**
- **…is very fast to train, can use multiple threads.**
- **…can easily scale to huge data and very large word and context vocabularies.**