



Department of Computer Science
UNIVERSITY OF COLORADO **BOULDER**



Distributional Semantics

Advanced Machine Learning for NLP

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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**

 **Pulse**

Automatically exported from code.google.com/p/word2vec

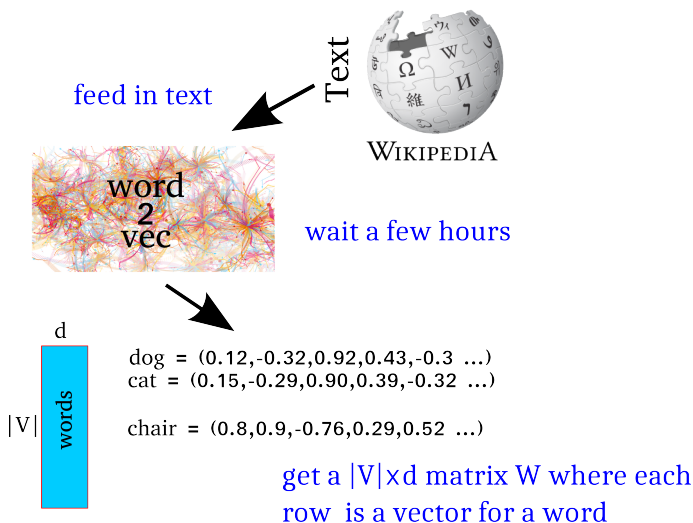
 **42 commits**

 **2 branches**

 **0 releases**

Branch: **master** ▼

New pull request



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*:

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

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

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

- 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.

Working with Dense Vectors

Finding the most similar words to \vec{dog}

- Compute the similarity from word \vec{v} to all other words.
- This is a **single matrix-vector product**: $W \cdot \vec{v}^T$

The diagram illustrates the matrix-vector product $W \cdot \vec{v}^T$ to find word similarities. It shows a matrix W of size $|V| \times d$ and a vector \vec{v}^T of size $d \times 1$. The result is a vector of similarities of size $1 \times |V|$.

The matrix W is represented by a blue vertical bar with the following words listed vertically: cat, chair, june, sun, bark, ..., ..., eat. The dimension d is indicated above the bar, and $|V|$ is indicated to the left.

The vector \vec{v}^T is represented by a small blue vertical bar with the word "dog" next to it. The dimension d is indicated above the bar.

The result is a horizontal bar with the following values: 0.9, -0.3, -0.1, -0.9, 0.3, ..., ..., 0.2. The dimension $1 \times |V|$ is indicated below the bar.

The equation is summarized as:

$$W \quad \vec{v}^T = \text{similarities}$$
$$|V| \times d \quad d \times 1 \quad 1 \times |V|$$

Working with Dense Vectors

Finding the most similar words to \vec{dog}

- Compute the similarity from word \vec{v} to all other words.
- This is a **single matrix-vector product**: $W \cdot \vec{v}^T$

The diagram illustrates the matrix-vector product $W \cdot \vec{v}^T$ to find word similarities. On the left, a matrix W of size $|V| \times d$ is shown as a blue vertical rectangle. It contains the words: cat, chair, june, sun, bark, ..., ..., eat. Above the first row is the label 'd'. To the left of the matrix is the label $|V|$. In the center, a vector \vec{v}^T of size $d \times 1$ is shown as a small blue vertical rectangle labeled 'dog'. To the right of the vector is an equals sign. Further right, a row of similarity values is shown in a pink horizontal rectangle, with the first few values being 0.9, -0.3, -0.1, -0.9, 0.3, ..., ..., 0.2. Below this row are the words: cat, chair, june, sun, bark, ..., ..., eat. Below the matrix and vector, the dimensions are given: $|V| \times d$ for W , $d \times 1$ for \vec{v}^T , and $1 \times |V|$ for the result 'similarities'.

$$\begin{matrix} & d \\ \begin{matrix} |V| \\ \text{cat} \\ \text{chair} \\ \text{june} \\ \text{sun} \\ \text{bark} \\ \dots \\ \dots \\ \text{eat} \end{matrix} & \begin{matrix} \text{dog} \end{matrix} & = & \begin{matrix} 0.9 & -0.3 & -0.1 & -0.9 & 0.3 & \dots & \dots & 0.2 \end{matrix} \\ & & & \begin{matrix} \text{cat} \\ \text{chair} \\ \text{june} \\ \text{sun} \\ \text{bark} \\ \dots \\ \dots \\ \text{eat} \end{matrix} \end{matrix}$$
$$\begin{matrix} W & \vec{v}^T & = & \text{similarities} \\ |V| \times d & d \times 1 & & 1 \times |V| \end{matrix}$$

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

Working with Dense Vectors

Finding the most similar words to \vec{d}_{dog}

- Compute the similarity from word \vec{v} to all other words.
- This is a **single matrix-vector product**: $W \cdot \vec{v}^T$

The diagram illustrates the matrix-vector product $W \cdot \vec{v}^T$ to find word similarities. On the left, a matrix W of size $|V| \times d$ is shown as a blue vertical rectangle. It contains the words: cat, chair, june, sun, bark, ..., ..., eat. Above the first row is the label 'd'. To the left of the matrix is the label $|V|$. In the center, a vector \vec{v}^T of size $d \times 1$ is shown as a small blue vertical rectangle, labeled 'dog' below it. To the right of the vector is an equals sign followed by a horizontal pink rectangle representing the resulting vector of similarities, of size $1 \times |V|$. This vector contains the values: 0.9, -0.3, -0.1, -0.9, 0.3, ..., ..., 0.2. Below the pink rectangle, the words cat, chair, june, sun, bark, ..., ..., eat are listed, aligned with the corresponding similarity values.

$$\begin{matrix} & d \\ & \text{cat} \\ & \text{chair} \\ & \text{june} \\ & \text{sun} \\ & \text{bark} \\ & \dots \\ & \dots \\ & \text{eat} \\ |V| \times d & \begin{matrix} \text{dog} \\ d \times 1 \end{matrix} & = & \begin{matrix} 0.9 & -0.3 & -0.1 & -0.9 & 0.3 & \dots & \dots & 0.2 \\ 1 \times |V| \end{matrix} \\ W & \vec{v}^T & = & \text{similarities} \\ |V| \times d & d \times 1 & & 1 \times |V| \end{matrix}$$

- Result is a $|V|$ sized vector of similarities.
- Take the indices of the k -highest values.
- **FAST!** for 180k words, $d=300$: $\sim 30\text{ms}$

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

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.
- 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?

How does word2vec work?

word2vec implements several different algorithms:

Two training methods

- Negative Sampling
- Hierarchical Softmax

Two context representations

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

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- **Negative Sampling**
- Hierarchical Softmax

Two context representations

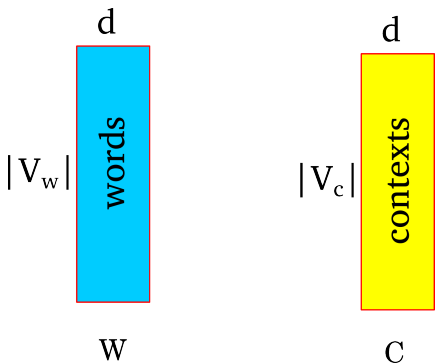
- Continuous Bag of Words (CBOW)
- **Skip-grams**

We'll focus on skip-grams with negative sampling

intuitions apply for other models as well

How does word2vec work?

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



How does word2vec work?

While more text:

- Extract a word window:

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

c_1 c_2 c_3 w c_4 c_5 c_6

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

How does word2vec work?

While more text:

- Extract a word window:

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

c_1 c_2 c_3 w c_4 c_5 c_6

- 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'

[a cow or **comet** close to calving]

c_1 c_2 c_3 w' c_4 c_5 c_6

- 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**

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.

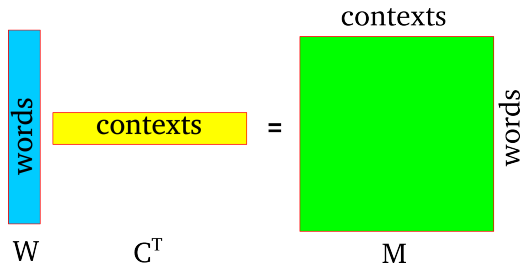
At the end, word2vec throws away C and returns W .

Reinterpretation

Imagine we didn't throw away C . Consider the product WC^T

Reinterpretation

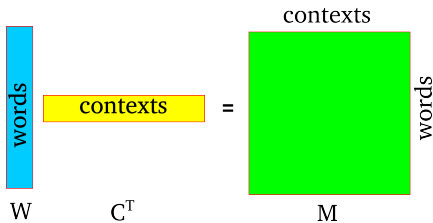
Imagine we didn't throw away C . Consider the product WC^T



The result is a matrix M in which:

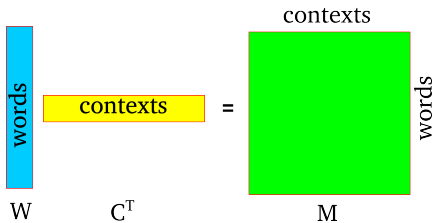
- Each row corresponds to a word.
- Each column corresponds to a context.
- Each cell: $w \cdot c$, association between word and context.

Reinterpretation



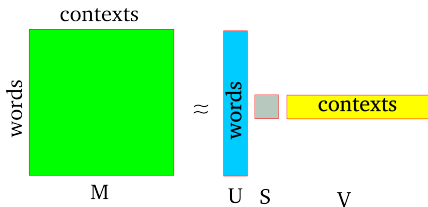
Does this remind you of something?

Reinterpretation



Does this remind you of something?

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, in submission) we can get SVD to perform just as well as `word2vec`.

Relation between SVD and word2vec

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Just like SVD.

With few tricks (Levy, Goldberg and Dagan, in submission) 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.**