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

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

Branch: master  New pull request
word2vec

feed in text

Text

WIKIPEDIA

wait a few hours

d

\begin{align*}
dog &= (0.12, -0.32, 0.92, 0.43, -0.3, \ldots) \\
cat &= (0.15, -0.29, 0.90, 0.39, -0.32, \ldots) \\
chair &= (0.8, 0.9, -0.76, 0.29, 0.52, \ldots) \\
\end{align*}

get a $|V| \times d$ 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, ramlal, safed

- **teva**
  - pfizer, schering-plough, novartis, astrazeneca, glaxosmithkline, sanofi-aventis, mylan, sanofi, genzyme, pharmacia
Word Similarity

- Similarity is calculated using cosine similarity:
  \[
  \text{sim}(\vec{\text{dog}}, \vec{\text{cat}}) = \frac{\vec{\text{dog}} \cdot \vec{\text{cat}}}{\|\vec{\text{dog}}\| \|\vec{\text{cat}}\|}
  \]

- For normalized vectors (\(\|x\| = 1\)), this is equivalent to a dot product:
  \[
  \text{sim}(\vec{\text{dog}}, \vec{\text{cat}}) = \vec{\text{dog}} \cdot \vec{\text{cat}}
  \]

- Normalize the vectors when loading them.
Working with Dense Vectors

Finding the most similar words to $\mathbf{d}_\mathbf{og}$

- Compute the similarity from word $\mathbf{v}$ to all other words.
Working with Dense Vectors

**Finding the most similar words to \( \mathbf{dog} \)**

- Compute the similarity from word \( \mathbf{v} \) to all other words.
- This is a **single matrix-vector product**: \( W \cdot \mathbf{v}^\top \)

\[
\begin{align*}
\text{W} & \in |V| \times d \\
\text{v} & \in d \times 1 \\
\text{W} \cdot \text{v}^\top & = \text{similarities} \\
|V| & \in 1 \times |V|
\end{align*}
\]
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**: $W \cdot \vec{v}^T$

```
| V | =
| d |
| cat | 0.9 |
| chair | -0.3 |
| june | -0.1 |
| sun | -0.9 |
| bark | 0.3 |
| ... | .... |
| eat | 0.2 |

$W$ | $V \times d$ | $d \times 1$ | similarities | $1 \times |V|$
```

- 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 $\mathbf{\hat{d}og}$

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

\[
\begin{array}{c}
\text{cat} \\
\text{chair} \\
\text{june} \\
\text{sun} \\
\text{bark} \\
\ldots \\
\text{...} \\
\text{...} \\
\text{eat} \\
\end{array}
\begin{array}{c}
\begin{array}{c}
\text{dog} \\
d \\
\end{array}
\begin{array}{c}
\begin{array}{c}
W \\
|V| \times d \\
\end{array}
\begin{array}{c}
\begin{array}{c}
\mathbf{\hat{v}}^T \\
d \times 1 \\
\end{array}
\begin{array}{c}
similarities \\
1 \times |V| \\
\end{array}
\end{array}
\end{array}
\end{array}
\]

- 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

```python
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:

\[ W \cdot \vec{\text{cat}} + W \cdot \vec{\text{dog}} + W \cdot \vec{\text{cow}} \]

- 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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- Continuous Bag of Words (CBOW)
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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:
  
  \[
  \text{A springer is[ a cow or } \textbf{heifer} \text{ close to calving ].}
  \]
  \[c_1 \quad c_2 \quad c_3 \quad w \quad c_4 \quad c_5 \quad c_6\]

- \(w\) 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 ].
  
  $c_1 \quad c_2 \quad c_3 \quad w \quad c_4 \quad c_5 \quad c_6$

- 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
How does word2vec work?

While more text:

- Extract a word window:
  A springer is [ a cow or heifer close to calving ].
  \[ c_1 \quad c_2 \quad c_3 \quad w \quad c_4 \quad c_5 \quad c_6 \]

- 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

- Create a corrupt example by choosing a random word \( w' \)
  [ a cow or comet close to calving ]
  \[ c_1 \quad c_2 \quad c_3 \quad w' \quad c_4 \quad c_5 \quad c_6 \]

- 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 $WC^\top$
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?

\[ W \cdot C^T = M \]
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, TACL 2015) we can get SVD to perform just as well as word2vec.
Relation between SVD and word2vec

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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.