Современные дистрибутивно-семантические модели и их применение в лингвистических исследованиях
День 2

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Тюмень, февраль 2018

Содержание

Representing documents

- Distributional approaches allow to extract semantics from unlabeled data at word level.
- But we also need to represent variable-length documents!
  - for classification,
  - for clustering,
  - for information retrieval (including web search).

Representing documents

- Can we detect semantically similar texts in the same way as we detect similar words?
- Yes we can!
- Nothing prevents us from representing sentences, paragraphs or whole documents (further we use the term 'document' for all these things) as dense vectors.
- After the documents are represented as vectors, classification, clustering or other data processing tasks become trivial.

Can we do without semantics?

Bag-of-words with TF-IDF

A very strong baseline approach for document representation, hard to beat by modern methods:

1. Extract vocabulary V of all words (terms) in the training collection consisting of N documents;
2. For each term, calculate its document frequency: in how many documents it occurs (df);
3. Represent each document as a sparse vector of frequencies for all terms from V contained in it (tf);
4. For each value, calculate the weighted frequency wf using term frequency / inverted document frequency (TF-IDF):
    - $\mathrm{wf} = (1 + \log_{10}\mathrm{tf}) \times \log_{10}(\frac{\mathrm{N}}{\mathrm{df}})$
5. Use these weighted document vectors in your downstream tasks.

Representing documents

Bag-of-words problems

Unfortunately, simple bag-of-word does not take into account semantic relationships between linguistic entities.
No way to detect semantic similarity between documents which do not share words:

- California saw mass protests after the elections.
- Many Americans were anxious about the elected president.

It means we need more sophisticated semantically-aware distributed methods, like neural embeddings.

Содержание

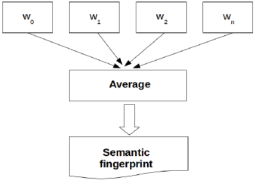
Distributed models: composing from word vectors

- Document meaning is composed of individual word meanings.
- Need to combine continuous word vectors into continuous document vectors.
- It is called a composition function.

Semantic fingerprints

- One of the simplest composition functions: an average vector $\vec{S}$ over vectors of all words $w_0 \ldots n$ in the document.
- We don't care about syntax and word order.
- If we already have a good word embedding model, this bottom-up approach is strikingly efficient and usually beats bag-of-words.
- Let's call it a 'semantic fingerprint' of the document.
- It is very important to remove stop words beforehand!

Distributed models: composing from word vectors



$$\vec{S} = \frac{1}{n} \times \sum_{i=0}^{n} \vec{w_n} \tag{1}$$

- You even don't have to average. Summing vectors is enough: cosine is about angles, not magnitudes.
- However, averaging makes difference in case of other distance metrics (Euclidean distance, etc).
- Also helps to keep things tidy and normalized (representations do not depend on document length).

Distributed models: composing from word vectors

Advantages of semantic fingerprints

- Semantic fingerprints work fast and reuse already trained models.
- Generalized document representations do not depend on particular words.
- They take advantage of 'semantic features' learned during the model training.
- Topically connected words collectively increase or decrease expression of the corresponding semantic components.
- Thus, topical words automatically become more important than noise words.

See more in [Kutuzov et al., 2016].

Distributed models: composing from word vectors

But...

However, for some problems such compositional approaches are not enough and we need to generate real document embeddings.

But how?

Содержание

Distributed models: training document vectors

Paragraph Vector

- [Le and Mikolov, 2014] proposed Paragraph Vector;
- primarily designed for learning sentence vectors;
- the algorithm takes as an input sentences/documents tagged with (possibly unique) identifiers;
- learns distributed representations for the sentences, such that similar sentences have similar vectors;
- so each sentence is represented with an identifier and a vector, like a word;
- these vectors serve as sort of document memories or document topics.

Not much evaluated (however, see [Hill et al., 2016] and [Lau and Baldwin, 2016])

Distributed models: training document vectors

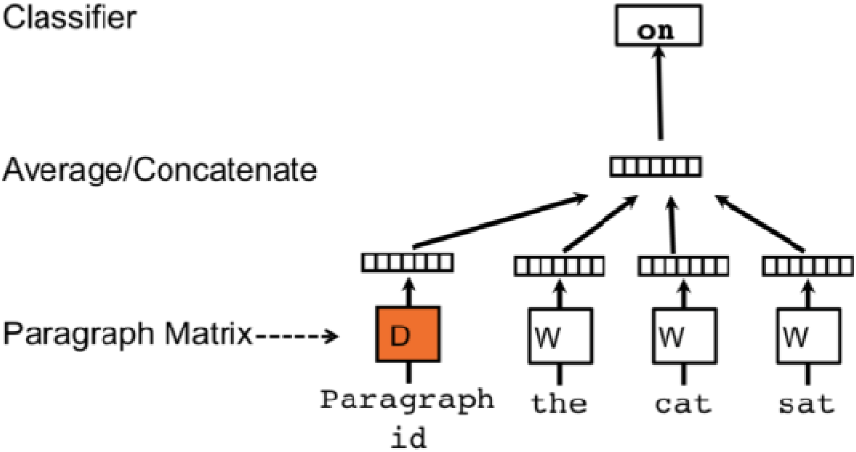
Paragraph Vector (aka doc2vec)

- implemented in Gensim under the name doc2vec;
- Distributed memory (DM) and Distributed Bag-of-words (DBOW) methods;
- PV-DM:
  - learn word embeddings in a usual way (shared by all documents);
  - randomly initialize document vectors;
  - use document vectors together with word vectors to predict the neighboring words within a pre-defined window;
  - minimize error;
  - the trained model can inference a vector for any new document (the model remains intact).
- PV-DBOW:
  - don't use sliding window at all;
  - just predict all words in the current document using its vector.

Contradicting reports on which method is better.

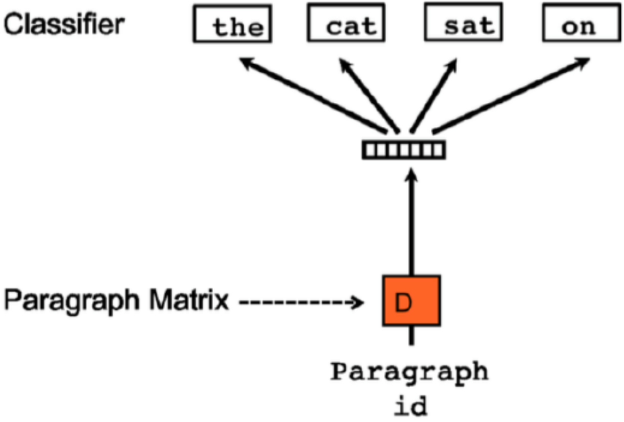
Distributed models: training document vectors

Paragraph Vector - Distributed memory (PV-DM)



Distributed models: training document vectors

Paragraph Vector - Distributed Bag-of-words (PV-DBOW)



Distributed models: training document vectors

Paragraph Vector (aka doc2vec)

- You train the model, then inference embeddings for the documents you are interested in.
- The resulting embeddings are shown to perform very good on sentiment analysis and other document classification tasks, as well as in IR tasks.
- Very memory-hungry: each sentence gets its own vector (many millions of sentences in the real-life corpora).
- It is possible to reduce the memory footprint by training a limited number of vectors: group sentences into classes.

Спасибо за внимание!
Вопросы?

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