INF5820

Distributional Semantics: Extracting Meaning from Data

Lecture 4

Beyond words: distributional representations of texts

Andrey Kutuzov
andreku@ifi.uio.no

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Contents

1. Brief recap
2. Problem description
3. Can we do without semantics?
4. Distributed models: composing from word vectors
5. Distributed models: training document vectors
6. In the next week

Brief recap

What we are going to cover today

- Problem of document classification;
- Traditional bag-of-words approach;
- Compositional distributed approaches;
- 'Proper' distributional approaches (document vectors).

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6 In the next week

Problem description

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- But we also need to represent variable-length documents!
  - for classification,
  - for clustering,
  - for information retrieval (including web search).

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- Unsupervised learning of distributed representations for documents are the topic of this lecture.

Note: this lecture does not cover sequence-to-sequence sentence modeling approaches based on RNNs (LSTM, GRU, etc). A good example of those is the Skip-Thought algorithm [Kiros et al., 2015].

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Note: this lecture does not cover sequence-to-sequence sentence modeling approaches based on RNNs (LSTM, GRU, etc). A good example of those is the Skip-Thought algorithm [Kiros et al., 2015]. We are concerned with comparatively simple algorithms conceptually similar to prediction-based distributional models for words.

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Can we do without semantics?

Bag-of-words with TF-IDF

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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):
5. $wf = (1 + log_{10} tf) \times log_{10}(\frac{N}{df})$
6. Use these weighted document vectors in your downstream tasks.

Can we do without semantics?

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- *Many Americans were anxious about the elected president.*

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

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Distributed models: composing from word vectors

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- If we already have a good word embedding model, this bottom-up approach is strikingly efficient and usually beats bag-of-words.
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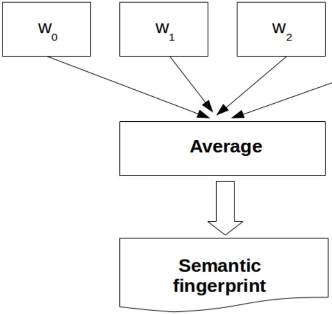
- It is very important to remove stop words beforehand!

Distributed models: composing from word vectors



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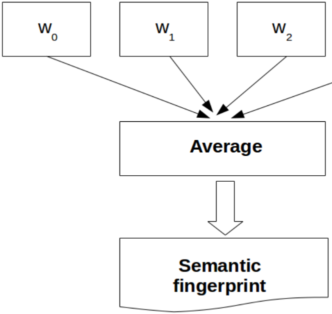

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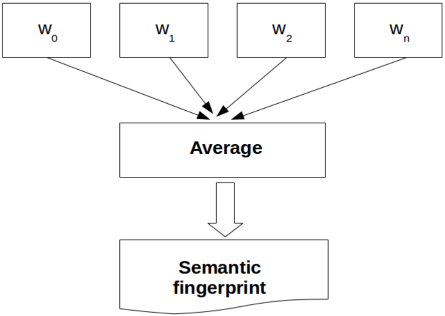

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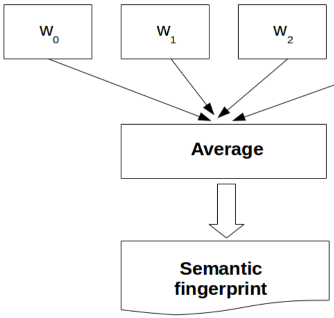

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- However, averaging makes difference in case of other distance metrics (Euclidean distance, etc).
- Also helps to keep things tidy and normalized.

Distributed models: composing from word vectors

Composition functions

- One can experiment with different combinations of word vectors, not only averaging:
  - Concatenation

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Composition functions

- One can experiment with different combinations of word vectors, not only averaging:
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  - etc...
- Can introduce word order knowledge by using n-grams instead of words.
- See [Mitchell and Lapata, 2010] for extensive description and evaluation of various compositional models.

Distributed models: composing from word vectors

Why semantic fingerprints are so efficient?

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

Distributed models: composing from word vectors

Deep inverse regression

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- drawback: you need separate models for each of your classes.

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.

Contents

1. Brief recap
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Distributed models: training document vectors

Many questions

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Distributed models: training document vectors

Many questions

- Should we treat the document as a single target unit surrounded by its counterparts?
- Or should we take into account the composing words, but go beyond simple composition functions?

Distributed models: training document vectors

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

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- PV-DBOW:
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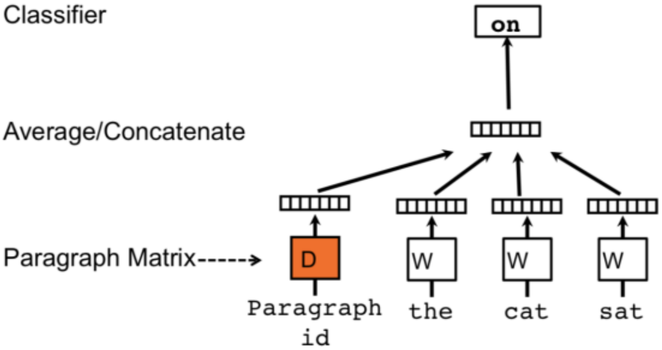
PV-DM seems to be generally better than PV-DBOW (not clear).

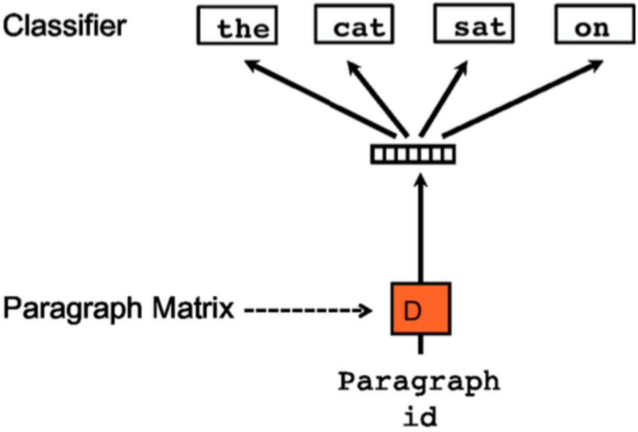
Distributed models: training document vectors

Paragraph Vector - Distributed memory (PV-DM)



Distributed models: training document vectors

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



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- 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.

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Distributed models: training document vectors

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For example:

interpret sentences or paragraphs as ‘words’ and train a common word embedding model.

The choice of an approach depends very much on your downstream task.

Questions?

INF5820
Distributional Semantics: Extracting Meaning from Data
Lecture 4
Beyond words: distributional representations of texts

Homework: obligatory assignment 3.

Contents

1 Brief recap

2 Problem description

3 Can we do without semantics?

4 Distributed models: composing from word vectors

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6 In the next week

In the next week

Kings and queens, men and women: semantic relations between word embeddings

- Distributional models contain not only words, but also relations between them;
- Why is that so?
- Mathematics behind this;
- Possible applications of semantic relations in distributional models;
- Projecting one model into another;
- etc...

Hill, F., Cho, K., and Korhonen, A. (2016).
Learning distributed representations of sentences from unlabelled data.
arXiv preprint arXiv:1602.03483.

Kiros, R., Zhu, Y., Salakhutdinov, R. R., Zemel, R., Urtasun, R., Torralba, A., and Fidler, S. (2015).
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