Week 8: Word Embeddings

Slava Mikhaylov

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Week 8 Outline

Word Embeddings

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Word Embeddings

- A geometric way to capture the “meaning” of a word via a low-dimensional vector.
- Currently used a lot in information retrieval (IR) and Natural Language Processing (NLP) to answer search queries or translate from one language to another.
- Basically, a 300-dimensional vector is used to capture the nuances of word meaning.

Properties of Word Embeddings

- Cosine similarity: the similarity between two words (as rated by humans on a [1,1] scale) correlates with the cosine of the angle between their vectors.
- The cosine for ‘milk‘ and ‘cow‘ may be 0.6; for ‘milk‘ and ‘stone‘ 0.2.

Properties of Word Embeddings

- Word embeddings can solve analogy relationships via linear algebra.
- `man : woman ::king : ??` can be solved looking for word w such that $v_{king} - v_w$ is most similar to $v_{man} - v_{woman}$

$$min||v_w - v_{king} + v_{man} - v_{woman}||^2$$

Properties of Word Embeddings

- Solves about 75% of standard word analogy questions.
- Unsupervised method. The embeddings are constructed using big unannotated corpus.
- No analogy specific training.
- From fMRI brain imaging analysis similar to be how the human brain encodes meaning (See Tom Mitchell et al. (2008). "Predicting Human Brain Activity Associated with the Meanings of Nouns." *Science*, 320, 1191.)

Computing Word embeddings

"You shall know a word by the company it keeps." (Firth, 1957)
`https://en.wikipedia.org/wiki/Distributional_semantics`

- Word vector is a succinct representation of the distribution of other words around this word.
- (cow, drink, babies, calcium: milk).

Computing Word embeddings

- Suppose the dictionary has N distinct words (in practice, $N = 100,000$).
- Take a very large text corpus (e.g., Wikipedia) and let $Count_5(w_1, w_2)$ be the number of times w_1 and w_2 occur within a distance 5 of each other in the corpus.
- Then the word embedding for a word w is a vector of dimension N, with one coordinate for each dictionary word.
- The coordinate corresponding to word w_2 is $Count_5(w, w_2)$.
- You can also extend it to cooccurence of w with ngrams.

Computing Word embeddings

- This embedding uses high-dimensional vectors (100,000-dimensional).
- We can reduce dimensionality by taking the rank-300 singular value decomposition (SVD).
- Method used directly in Latent Semantic Indexing (LSI). `http://lsa.colorado.edu/papers/JASIS.lsi.90.pdf`
- We can improve the method by replacing the counts with their logs. That's Latent Semantic Analysis (LSA). `http://lsa.colorado.edu/papers/plato/plato.annote.html`.

Vector Space Models

- Insight from LSA: Dimension reduction via SVD improves quality of embedding. Level of average American school kid.
- Vector Space Models are modifications on the above.
- Embeddings also improve with various reweights: TF-IDF, PMI, log, etc.
- See overview of VSM in Turney and Pantel paper: `https://www.jair.org/media/2934/live-2934-4846-jair.pdf`.

Word2Vec

- Introduced in 2013 by Mikolov et al. at Google `https://code.google.com/archive/p/word2vec/`.
- Related to neural net models for language.
- Word embedding corresponds to the neural net's internal representation of the word. See here for more: `http://colah.github.io/posts/2014-07-NLP-RNNs-Representations/`.

Word2Vec

$$Pr[w|w_1, w_2, \ldots, w_5] \propto exp(v_w \cdot (\frac{1}{5}\sum_i v_{w_i}))$$

- The left hand side gives the empirical probability that word w occurs in the text conditional on the last five words being w_1 through w_5.

Making sense of word2vec

- Original papers are not clear why they actually work.
- Levy and Goldberg (in a series of papers) explain word2vec: `https://levyomer.wordpress.com`.
- They show word2vec to be a modern version of older vector space models.

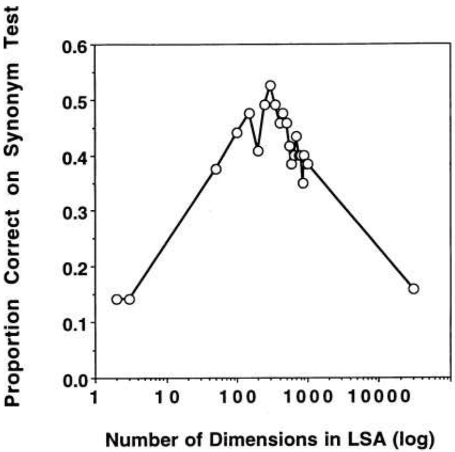
Making sense of word2vec

- Another approach, by Pennington et al. (Standord NLP group) suggest a GLoVe model (`http://nlp.stanford.edu/projects/glove/`).
- They use a weighted-SVD strategy to find word embeddings.
- They also provide an intuitive explanation why these embeddings solve word analogy tasks.

Making sense of word2vec

- For a more in-depth explanation of "black magic" see "RAND-WALK: A Latent Variable Model Approach to Word Embeddings" `https://arxiv.org/abs/1502.03520`.
- They provide a new generative model for text, and a clearer insight into the causative relationship between word meanings and the cooccurence probabilities.
- Intuitively, corpus generation is a dynamic process driven by the random walk of a *discourse* vector.
- Direction of this discourse vector represents what is being talked about.
- Each word is then related to this discourse vector through a time-invariant latent vector that captures its correlations with the discourse vector.

Low dimensional embeddings vs high dimensional embeddings



Performance curve of word embeddings

- Too few parameters make the model incapable of fitting to the signal;
- Too many parameters, and it starts overfitting (e.g., fitting to noise instead of the signal).
- Thus the dimension constraint acts as a regularizer for the optimization.

Performance curve of word embeddings

- Arora et al. "RAND-WALK" paper shows that relations correspond to directions (unlike Levy and Goldberg but closer to GLoVe).
- Particularly for semantic analogies.
- Using linear algebra and enough examples we can e.g. predict new leaders based on the list of current leaders.

Word embeddings in R

- text2vec `http://text2vec.org`
- textmineR `https://github.com/TommyJones`
- wordVectors `https://github.com/bmschmidt`

Examples of projects

- Word embeddings worked example with wordVectors: `http://bookworm.benschmidt.org/posts/2015-10-25-Word-Embeddings.html`.
- Pablo Barbera's workshop: `https://github.com/pablobarbera/data-science-workshop`
- Wikileaks: `http://rpubs.com/Custer/wikileaks` and Michael Gill and Arthur Spirling paper in Political Analysis `http://pan.oxfordjournals.org/content/23/2/299.short`.
- Museum collections: `https://rpubs.com/alyssafahringer/176732`.