annotated version

Machine Learning Course - CS-433

Text Representation Learning

Nov 21, 2019

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EPFL

Motivation

Finding numerical representations for words is fundamental for all machine learning methods dealing with text data.

Goal: For each word, find mapping (embedding)

$$w_i \mapsto \mathbf{w}_i \in \mathbb{R}^K$$

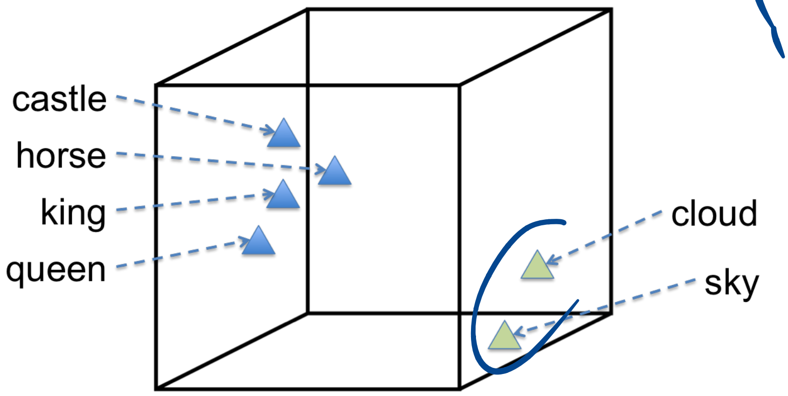
← vocabulary size

$$\text{word } w_i \rightarrow \begin{pmatrix}0\\ \vdots\\ 0\\ 1\\ 0\\ \vdots\\ 0\end{pmatrix} \leftarrow i$$

„Bag of words"

$$\begin{pmatrix}\vdots\\ 1\\ \vdots\\ 1\\ \vdots\\ 1\\ \vdots\end{pmatrix}$$

Representation should capture semantics of the word.

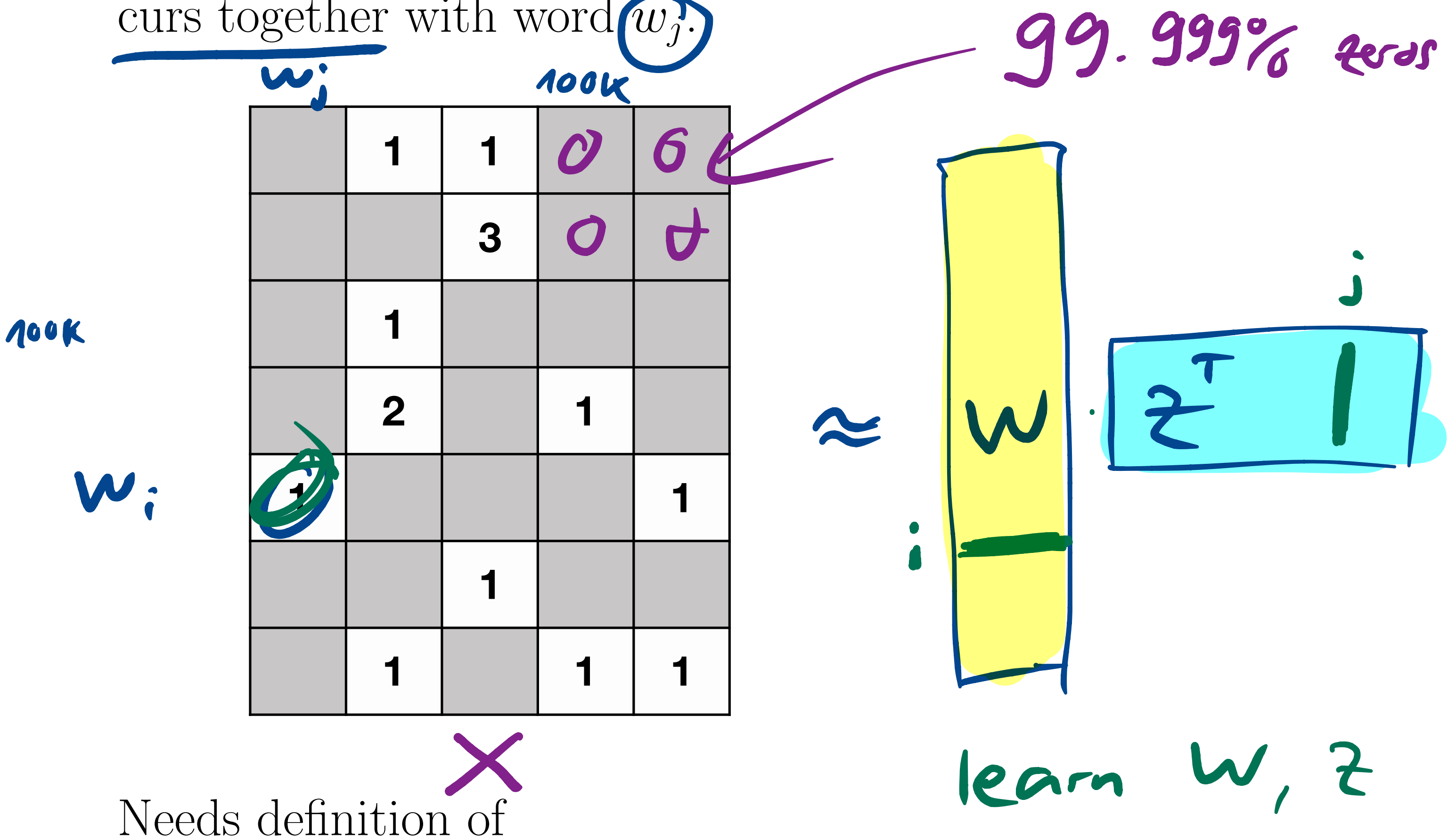


Constructing good feature representations (= representation learning) benefits all ML applications.

The Co-Occurence Matrix

A big corpus of un-labeled text can be represented as the co-occurrence counts

n_{ij} := #contexts where word w_i occurs together with word w_j.



	1	1	0	0
		3	0	0
	1			
	2		1	
1				1
		1		
	1		1	1

Needs definition of

- Context e.g. document, paragraph, sentence, window
- Vocabulary
  $\mathcal{V} := \{w_1, \ldots, w_D\}$

D = 100K

For words $w_d = 1, 2, \ldots, D$ and context words $w_n = 1, 2, \ldots, N$, the co-occurence counts n_{ij} form a very sparse $D \times N$ matrix.

Typically D=N

Learning Word-Representations (Using Matrix Factorization)

Find a factorization of the co-occurence matrix!
Typically uses log of the actual counts, i.e. $x_{dn} := \log(n_{dn})$.

- GloVe
- word 2vec

We will aim to find $\mathbf{W}, \mathbf{Z}$ s.t.

$$\mathbf{X} \approx \mathbf{W}\mathbf{Z}^\top .$$

So for each pair of words (w_d, w_n), we try to 'explain' their co-occurence count by a numerical representation of the two words
- in fact by the inner product of the two feature vectors $\mathbf{W}_{d:}, \mathbf{Z}_{n:}$.

$$\min_{\mathbf{W},\mathbf{Z}} \ \mathcal{L}(\mathbf{W},\mathbf{Z}) := \frac{1}{2} \sum_{(d,n)\in\Omega} \overset{\text{fixed weighting}}{f_{dn}} \Big[\overset{\log(\text{co-occurrence}(d,n))}{x_{dn}} - (\mathbf{W}\mathbf{Z}^\top)_{dn} \Big]^2$$

where $\mathbf{W} \in \mathbb{R}^{D\times K}$ and $\mathbf{Z} \in \mathbb{R}^{N\times K}$ are tall matrices, having only $K \ll D, N$ columns.
The set $\Omega \subseteq [D] \times [N]$ collects the indices of non-zeros of the count matrix $\mathbf{X}$.
Each row of those matrices forms a representation of a word ($\mathbf{W}$) or a context word ($\mathbf{Z}$) respectively.

2014

GloVe

This model is called GloVe, and is a variant of word2vec.

Weights f_{dn}: Give "importance" of each entry. Choosing $f_{dn} := 1$ is ok. GloVe weight function:

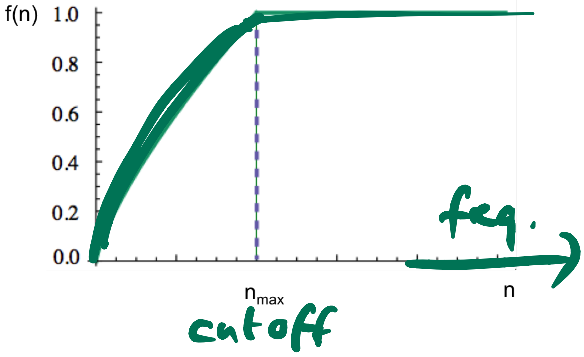
(Heuristic)

„growth rate"

$$f_{dn} := \min\left\{1, (n_{dn}/n_{\max})^{\alpha}\right\}, \quad \alpha \in [0;1] \quad \text{e.g. } \alpha = \frac{3}{4}$$

cut-off

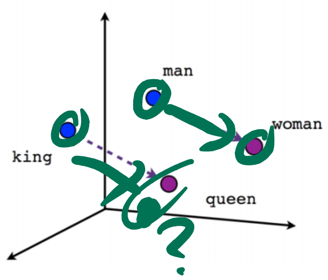
observed count



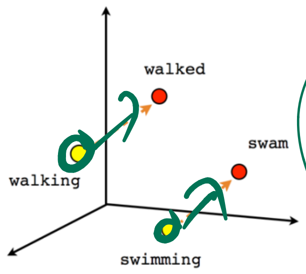
Choosing K

K e.g. 50, 100, 500

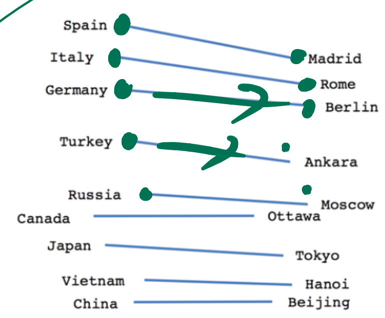
Word Analogies



Male-Female



Verb tense



Country-Capital

Newspapers			
New York	New York Times	Baltimore	Baltimore Sun
San Jose	San Jose Mercury News	Cincinnati	Cincinnati Enquirer
NHL Teams			
Boston	Boston Bruins	Montreal	Montreal Canadiens
Phoenix	Phoenix Coyotes	Nashville	Nashville Predators
NBA Teams			
Detroit	Detroit Pistons	Toronto	Toronto Raptors
Oakland	Golden State Warriors	Memphis	Memphis Grizzlies
Airlines			
Austria	Austrian Airlines	Spain	Spainair
Belgium	Brussels Airlines	Greece	Aegean Airlines
Company executives			
Steve Ballmer	Microsoft	Larry Page	Google
Samuel J. Palmisano	IBM	Werner Vogels	Amazon

Training

- Stochastic Gradient Descent (SGD) ← lab #10
- ~~Alternating Least-Squares (ALS)~~ not scalable

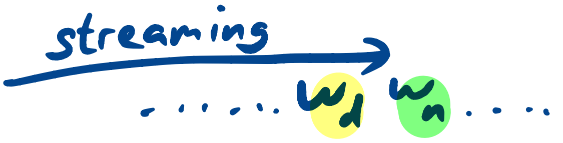
Open questions:

- Parallel and distributed training
- Does regularization help?

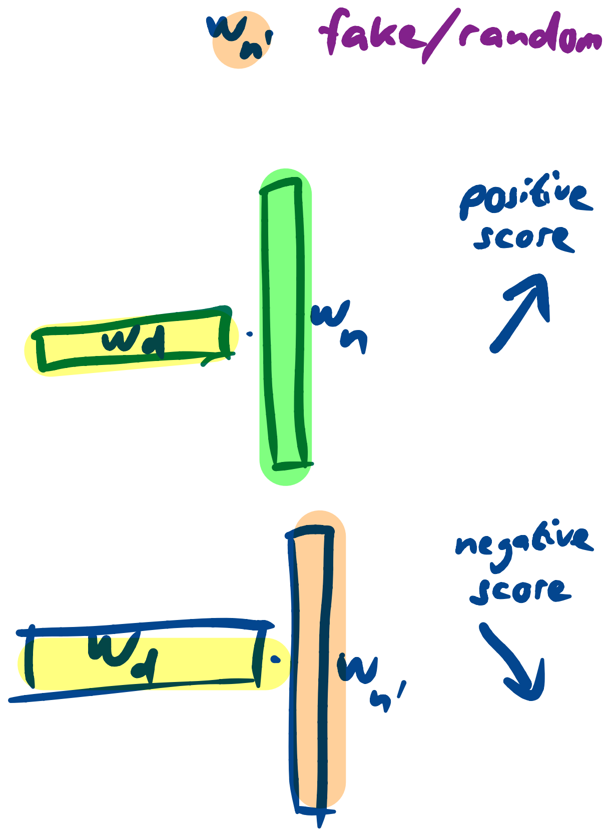
Alternative: Skip-Gram Model

2013

(Original word2vec)



Uses binary classification (logistic regression objective), to separate real word pairs (w_d, w_n) from fake word pairs. Same inner product score = matrix factorization.



Given w_d, a context word w_n is

- real = appearing together in a context window of size 5
- fake = any word $w_{n'}$ sampled randomly: Negative sampling (also: Noise Contrastive Estimation)

Language Models

Unsupervised training:

Train a classifier to predict the continuation (next word) of a text

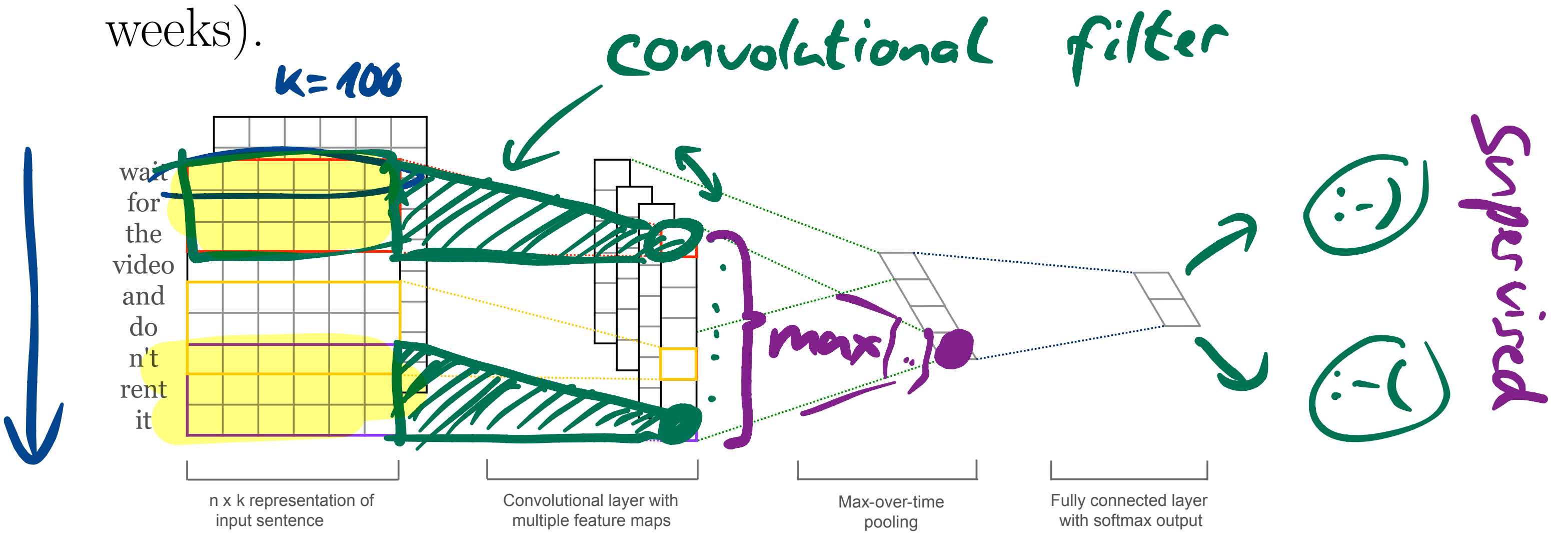
$w_1, w_2 \ldots, w_{10},$ ↑ next word

- Multi-class:
  Use soft-max loss function with a large number of classes D =vocabulary size
- Binary classification: Scalable alternative
  Predict if next word is real or fake (i.e. a negative sample, as above)

Impressive recent progress using large models, such as transformers
(e.g. GPT-2
https://transformer.huggingface.co/doc/gpt2-large)

Learning Representations of Sentences & Documents

Supervised: For a supervised task (e.g. predicting the emotion of a tweet), we can use matrix-factorization (below) or convolutional neural networks (see next weeks).


convolutional filter
k=100
wait
for
the
video
and
do
n't
rent
it
max(...)
:-)
:-(
supervised
n x k representation of input sentence
Convolutional layer with multiple feature maps
Max-over-time pooling
Fully connected layer with softmax output

→ SemEval competition for tweet classification.

Unsupervised:

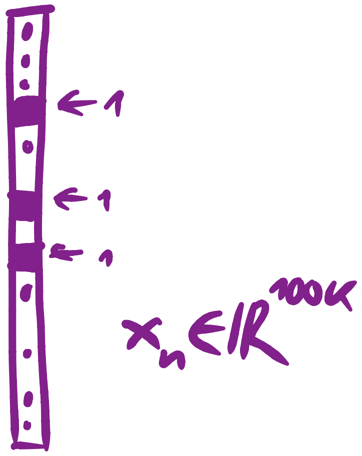
- Adding or averaging (fixed, given) word vectors
- Training word vectors such that adding/averaging works well (sent2vec)
- Direct unsupervised training for sentences (appearing together with context sentences) instead of words

FastText

supervised sentence classification

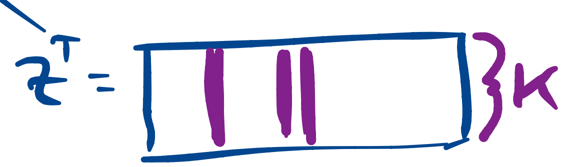
Matrix factorization to learn document/sentence representations (supervised).

Given a sentence $s_n = (w_1, w_2, \dots, w_m)$, let $\mathbf{x}_n \in \mathbb{R}^{|\mathcal{V}|}$ be the bag-of-words representation of the sentence.



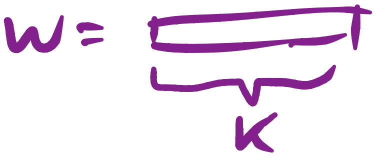
$$\min_{\mathbf{W},\mathbf{Z}} \mathcal{L}(\mathbf{W},\mathbf{Z}) := \sum_{s_n \text{ a sentence}} f(y_n \underline{\mathbf{W}\mathbf{Z}^\top \mathbf{x}_n)}$$

where $\mathbf{W} \in \mathbb{R}^{1 \times K}$, $\mathbf{Z} \in \mathbb{R}^{|\mathcal{V}| \times K}$ are the variables, and the vector $\mathbf{x}_n \in \mathbb{R}^{|\mathcal{V}|}$ represents our n-th training sentence.



e.g. logistic

Here f is a linear classifier loss function, and $y_n \in \{\pm 1\}$ is the classification label for sentence $\mathbf{x}_n$.



learn both W, Z

Further Pointers

1. word2vec:
   code: code.google.com/p/word2vec/
   paper:
   "Distributed representations of words and phrases and their compositionality" - T Mikolov, I Sutskever, K Chen, GS Corrado, J Dean. NIPS 2013

2. GloVe:
   code and vectors: nlp.stanford.edu/projects/glove/
   paper:
   "GloVe: Global Vectors for Word Representation" - Pennington, J., Socher, R., Manning, C. D.. EMNLP 2014

3. Write with transformers:
   code and demo: transformer.huggingface.co/doc/gpt2-large

4. FastText & sent2vec
   code: github.com/facebookresearch/fastText
   papers:
   "Bag of Tricks for Efficient Text Classification" - Joulin, A., Grave, E., Bojanowski, P., Mikolov, T. - EC-ACL, 2017.
   "Enriching Word Vectors with Subword Information" - Bojanowski, P., Grave, E., Joulin, A., Mikolov, T. - TACL, 2017.
   "Unsupervised Learning of Sentence Embeddings using Compositional n-Gram Features" - Pagliardini, M., Gupta, P., Jaggi, M. NAACL 2018.