annotated version

Machine Learning Course - CS-433

Text Representation Learning

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Motivation

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

„bag of words"

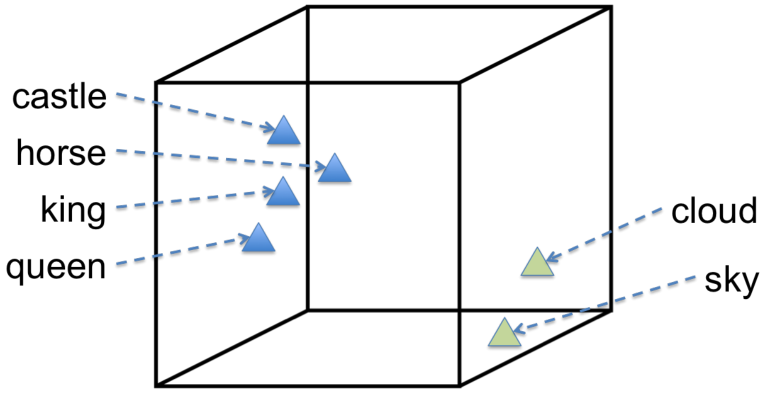
$$w_i = \begin{pmatrix}0\\ \vdots\\ 0\\ 1\\ 0\\ \vdots\\ 0\end{pmatrix} \leftarrow \text{position } i \quad \in \mathbb{R}^K$$

one-hot

Goal: For each word, find mapping (embedding)

$$\overset{\text{word}}{w_i} \mapsto \overset{\text{features}}{\mathbf{w}_i} \in \mathbb{R}^{K} \leftarrow \text{vocabulary size}$$

Representation should capture semantics of the word.



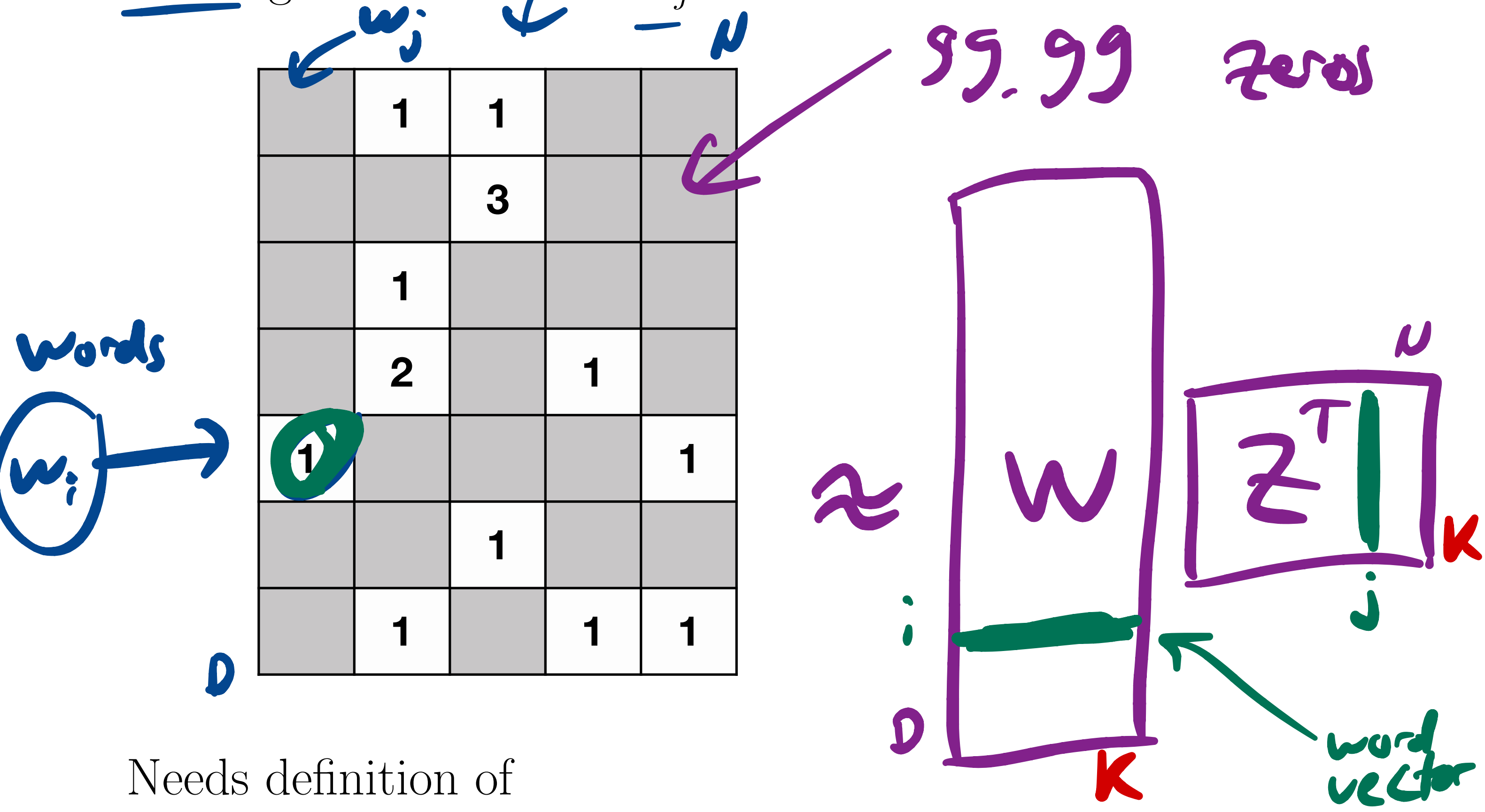
Constructing good feature representations (= representation learning) benefits all ML applications.

The Co-Occurence Matrix

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

Context

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



	1	1		
		3		
	1			
	2		1	
1				1
		1		
	1		1	1

Needs definition of

- Context e.g. document, paragraph, sentence, window = „5 words apart"
- Vocabulary $\mathcal{V} := \{w_1, \dots, w_D\}$

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

D=N in reality

Learning Word-Representations (Using Matrix Factorization)

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

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

$$\underbrace{\mathbf{X}}_{\text{co-occurrence matrix}} \approx \mathbf{W}\mathbf{Z}^\top .$$

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 $\mathbf{W}_{d:}, \mathbf{Z}_{n:}$.

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

same as netflix

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.

- word2vec 2013
- GloVe 2014

GloVe

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

„Heuristic"

→ GloVe

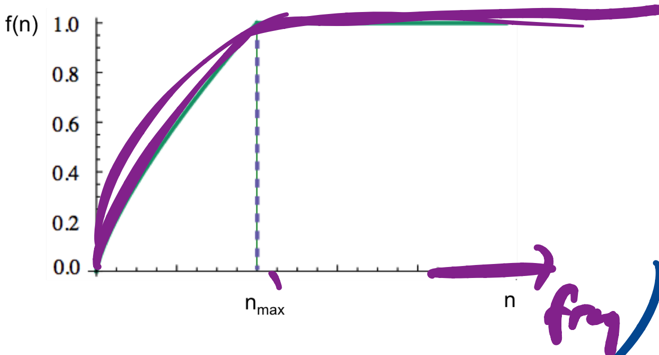
Weights f_{dn}: Give "importance" of each entry. Choosing $f_{dn} := 1$ is ok. GloVe weight function:

growth rate

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

cut-off

(manual hyperparam)



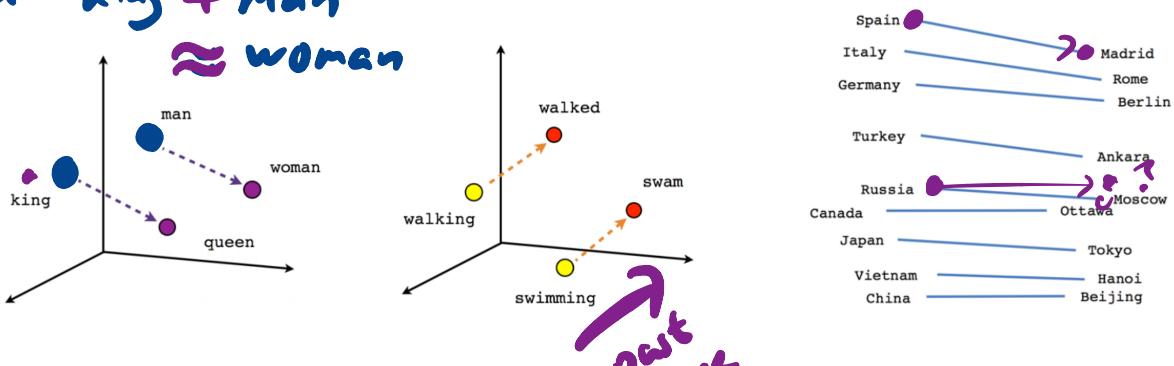
Choosing K

K e.g. 50, 100, 500

768

Word Analogies

queen − king + man ≈ woman



Male-Female

Verb tense

Country-Capital

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

similarity queries

q → nearest word vector

Training

- Stochastic Gradient Descent (SGD) ← efficiency per step $O(k)$
- Alternating Least-Squares (ALS) see lab

Open questions:

- Parallel and distributed training
- Does regularization help?

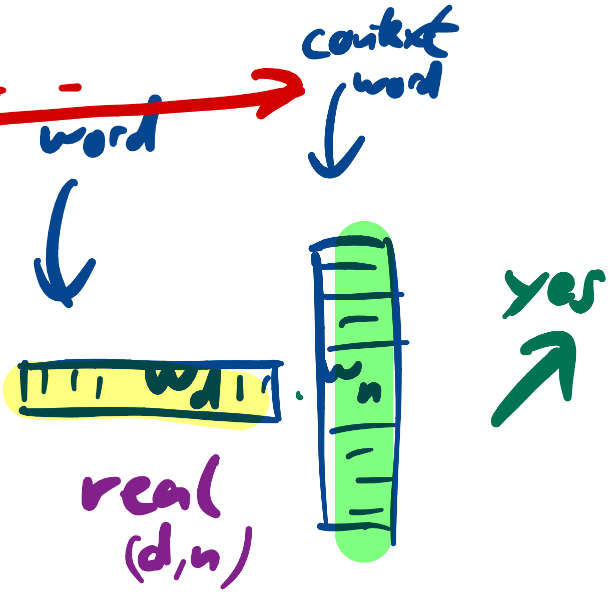
downside: precompute X (big)

Alternative: Skip-Gram Model

(Original word2vec)

streaming input text w_d w_n

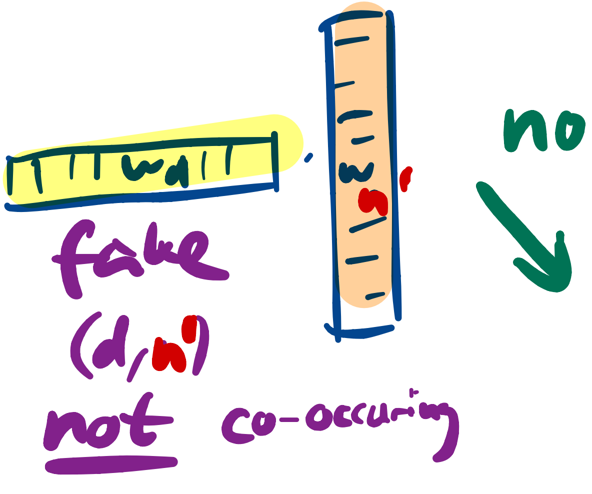
Uses binary classification (logistic regression objective), to separate real word pairs (w_d, w_n) from fake word pairs. Same inner product score = matrix factorization.



SGD

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)



Contrastive learning

$$\underbrace{w_1 \quad w_2 \quad w_3 \ldots w_n}\ \ldots\ \textcircled{?}$$

$$\to \boxed{ML} \to w_{n+1}$$

Language Models

Unsupervised training:

Can a model generate text? - train classifier to predict the continuation (next word) of given text

- Multi-class:
  Use soft-max loss function with a large number of classes D =vocabulary size
- Binary classification:
  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, GPT-3 ← 11 B params
https://transformer.huggingface.co/doc/gpt2-large)

use for ① text generation

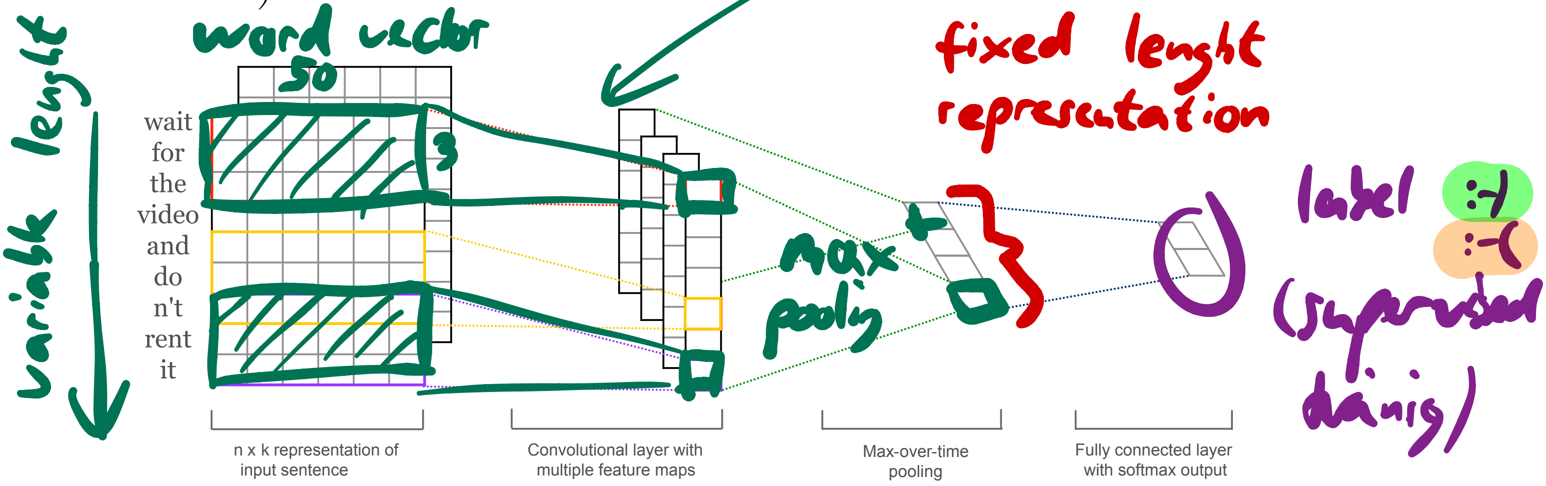
② get features

BERT

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).

CNN
convolutional
network



→ SemEval competition for tweet classification.

Unsupervised:

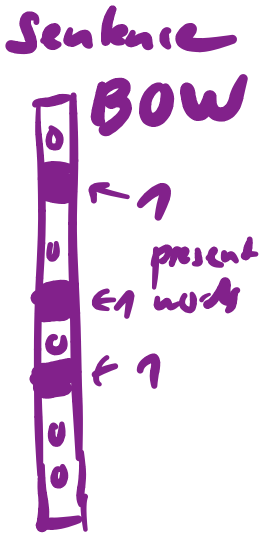
- Adding or averaging (fixed, given) word vectors
- Training word vectors such that adding/averaging works well
- Direct unsupervised training for sentences (appearing together with context sentences) instead of words

for supervised sentence classification

FastText

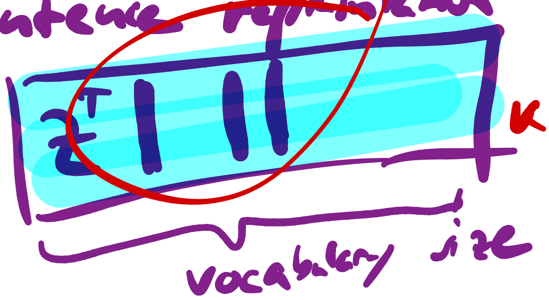
Matrix factorization to learn document/sentence representations (supervised).

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



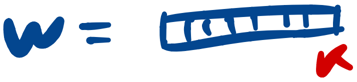
±1 label

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



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.

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



non-linear method

train with SGD

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.