Artificial Neural Networks and Deep Learning

- Word Embedding-

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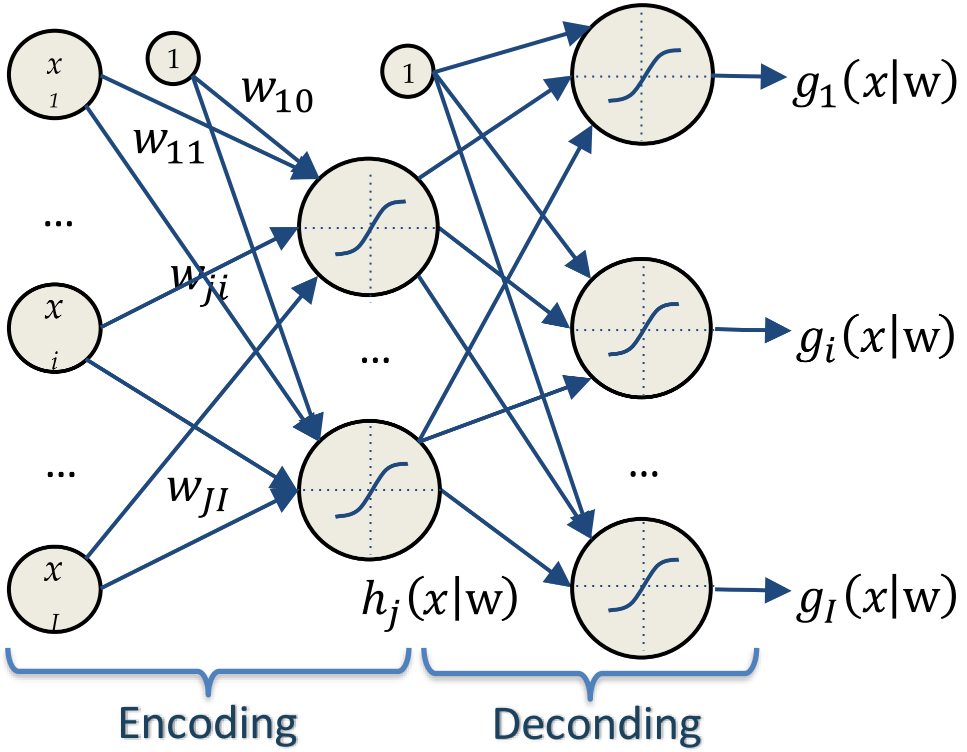
Neural Autoencoder Recall

Network trained to output the input (i.e., to learn the identity function)

- Limited number of units in hidden layers (compressed representation)
- Constrain the representation to be sparse (sparse representation)



$$x \in \Re^I \xrightarrow{enc} h \in \Re^J \xrightarrow{dec} g \in \Re^I$$

$$J \ll I$$

$$E = \underbrace{\|g_i(x_i|w) - x_i\|^2}_{\text{Reconstruction error}} + \underbrace{\lambda \sum_j \left| h_j\left(\sum_i w_{ji}^{(1)} x_i\right)\right|}_{\text{Sparsity term}}$$

$$g_i(x_i|\mathrm{w}) \sim x_i \qquad h_j(x_i|\mathrm{w}) \sim 0$$

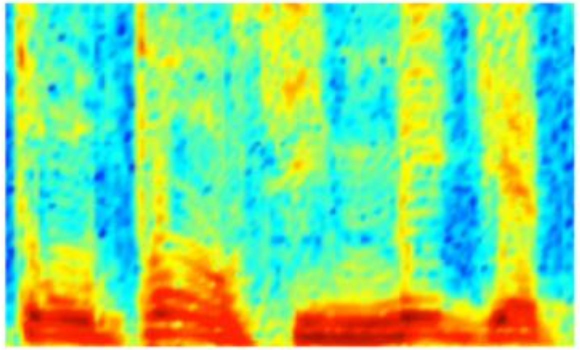
Word Embedding Motivation

Natural language processing treats words as discrete atomic symbols

- 'cat' is encoded as Id537
- 'dog' is encoded as Id143
- …

Items in a dictionary …

A document becomes a Bag of Words



Audio Spectrogram

DENSE

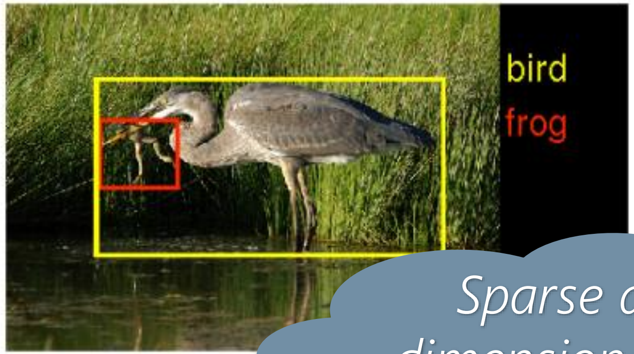


Image pixels

DENSE

Sparse and high dimensional -> Curse of Dimensionality!

0	0	0	0.2	0	0.7	0	0	0	...	...

Word, context, or document vectors

SPARSE

Encoding Text is a Serious Thing

Performance of real-world applications (e.g., chatbot, document classifiers, information retrieval systems) depends on input encoding:

Local representations

- N-grams —Language Model→
- Bag-of-words
- 1-of-N coding

Continuous representations

- Latent Semantic Analysis
- Latent Dirichlet Allocation
- Distributed Representations

Determine $P(s = w_1, \dots, w_k)$ in some domain of interest

$$P(s_k) = \prod_{i}^{k} P(w_i |\, w_1, \dots, w_{i-1})$$

In traditional n-gram language models "the probability of a word depends only on the context of n−1 previous words"

$$\hat{P}(s_k) = \prod_{i}^{k} P(w_i |\, w_{i-n+1}, \dots, w_{i-1})$$

Typical ML-smoothing learning process (e.g., Katz 1987):

- compute $\hat{P}(w_i |\, w_{i-n+1}, \dots, w_{i-1}) = \frac{\#w_{i-n+1}, \dots, w_{i-1}, w_i}{\#w_{i-n+1}, \dots, w_{i-1}}$
- smooth to avoid zero probabilities

N-gram Language Model: Curse of Dimensionality

Let’s assume a 10-gram LM on a corpus of 100.000 unique words

- The model lives in a 10D hypercube where each dimension has 100.000 slots
- Model training ↔ assigning a probability to each of the 100.000^{10} slots
- *Probability mass vanishes* → more data is needed to fill the huge space
- The more data, the more unique words! → Is not going to work …

In practice:

- Corpuses can have 10^6 unique words
- Contexts are typically limited to size 2 (trigram model), e.g., famous Katz (1987) smoothed trigram model
- With short context length a lot of information is not captured

N-gram Language Model: Word Similarity Ignorance

Let assume we observe the following similar sentences

- *Obama speaks to the media in Illinois*
- *The President addresses the press in Chicago*

With classic one-hot vector space representations

- speaks = [0 0 1 0 ... 0 0 0 0]
- addresses = [0 0 0 0 ... 0 0 1 0]

speaks ⊥ addresses

- obama = [0 0 0 0 ... 0 1 0 0]
- president = [0 0 0 1 ... 0 0 0 0]

obama ⊥ president

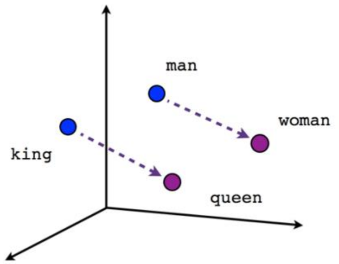
- illinois = [1 0 0 0 ... 0 0 0 0]
- chicago = [0 1 0 0 ... 0 0 0 0]

illinois ⊥ chicago

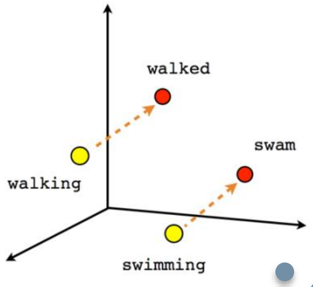
Word pairs share no similarity, and we need word similarity to generalize

Embedding

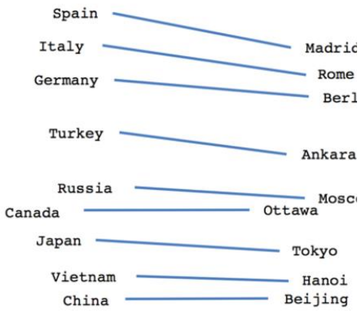
Any technique mapping a word (or phrase) from it's original high-dimensional input space (the body of all words) to a lower-dimensional numerical vector space - so one *embeds* the word in a different space



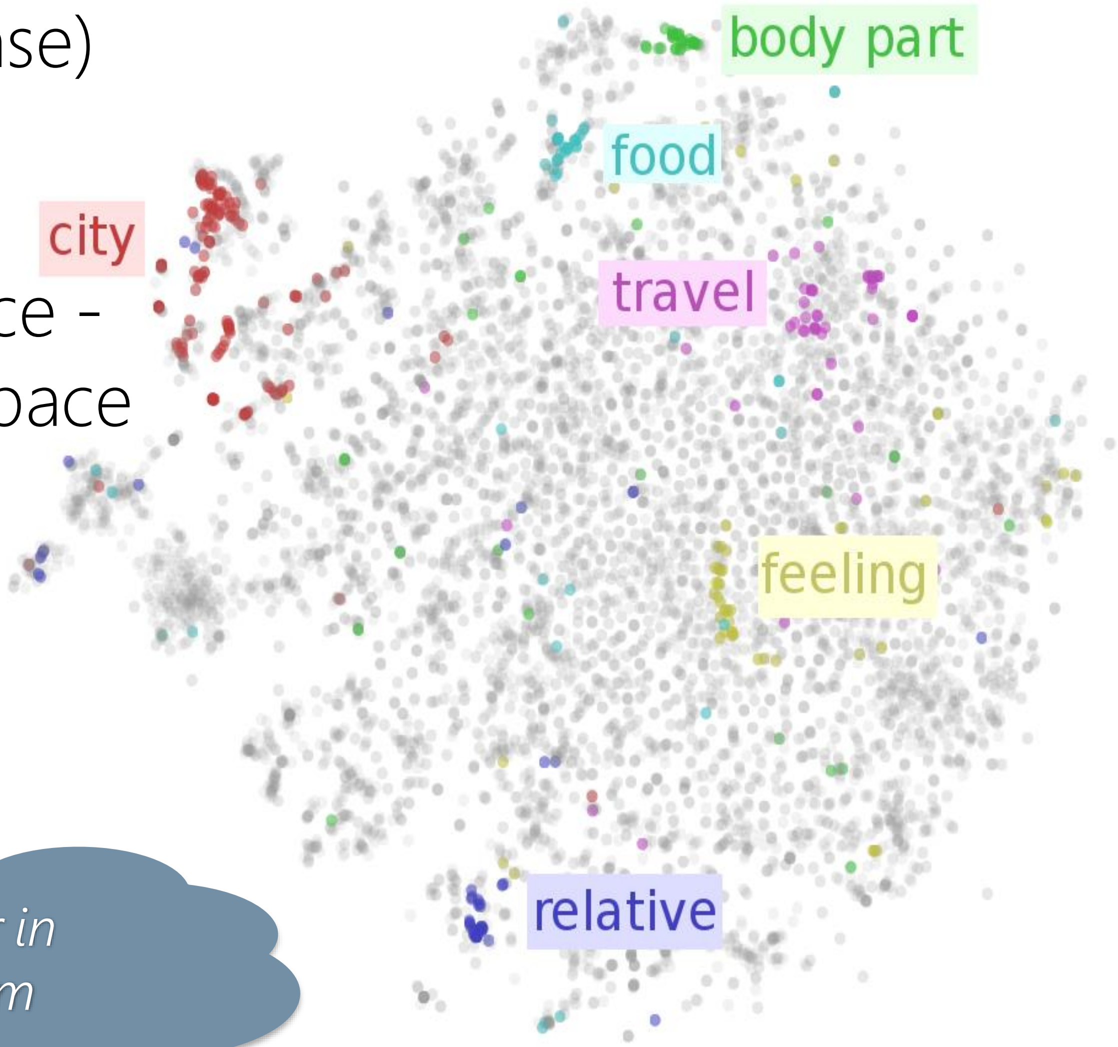
Male-Female



Verb tense



Closer points are closer in meaning and they form clusters ...



Word Embedding: Distributed Representation

Each unique word $\boldsymbol{w}$ in a vocabulary V (typically $\|V\| > 10^6$) is mapped to a continuous m-dimensional space (typically $100 < m < 500$)

$$w \in V \xrightarrow{mapping\ C} \Re^m$$

$$\text{obama} = \underbrace{\begin{array}{c} \begin{array}{ccc} w_1 & \text{obama} & w_V \end{array} \\ [0\ 0 \ldots 0\ 1\ 0 \ldots 0\ 0] \end{array}}_{\text{«one-hot» encoding}} \quad \Rightarrow \quad \text{obama} = \underbrace{\begin{array}{c} \begin{array}{cc} f_1 & f_m \end{array} \\ [0.12 \ldots -0.25] \end{array}}_{\text{feature vector}}$$

Fighting the curse of dimensionality with:

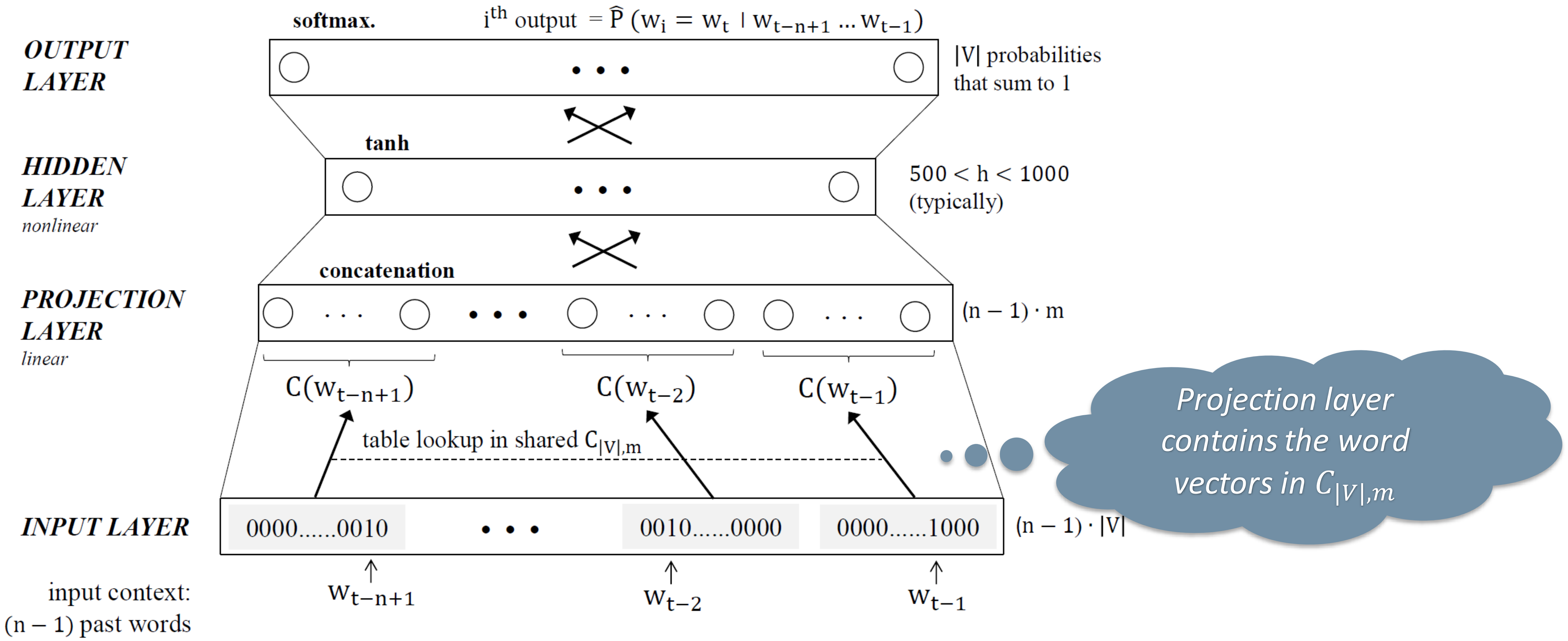
- Compression *(dimensionality reduction)*
- Smoothing *(discrete to continuous)*
- Densification *(sparse to dense)*

Similar words should end up to be close to each other in the feature space …

Neural Net Language Model (Bengio et al. 2003)

For each training sequence: input = (context, target) pair: $(w_{t-n+1} \dots w_{t-1}, w_t)$

objective: minimize $E = -\log \widehat{P}(w_t \mid w_{t-n+1} \dots w_{t-1})$



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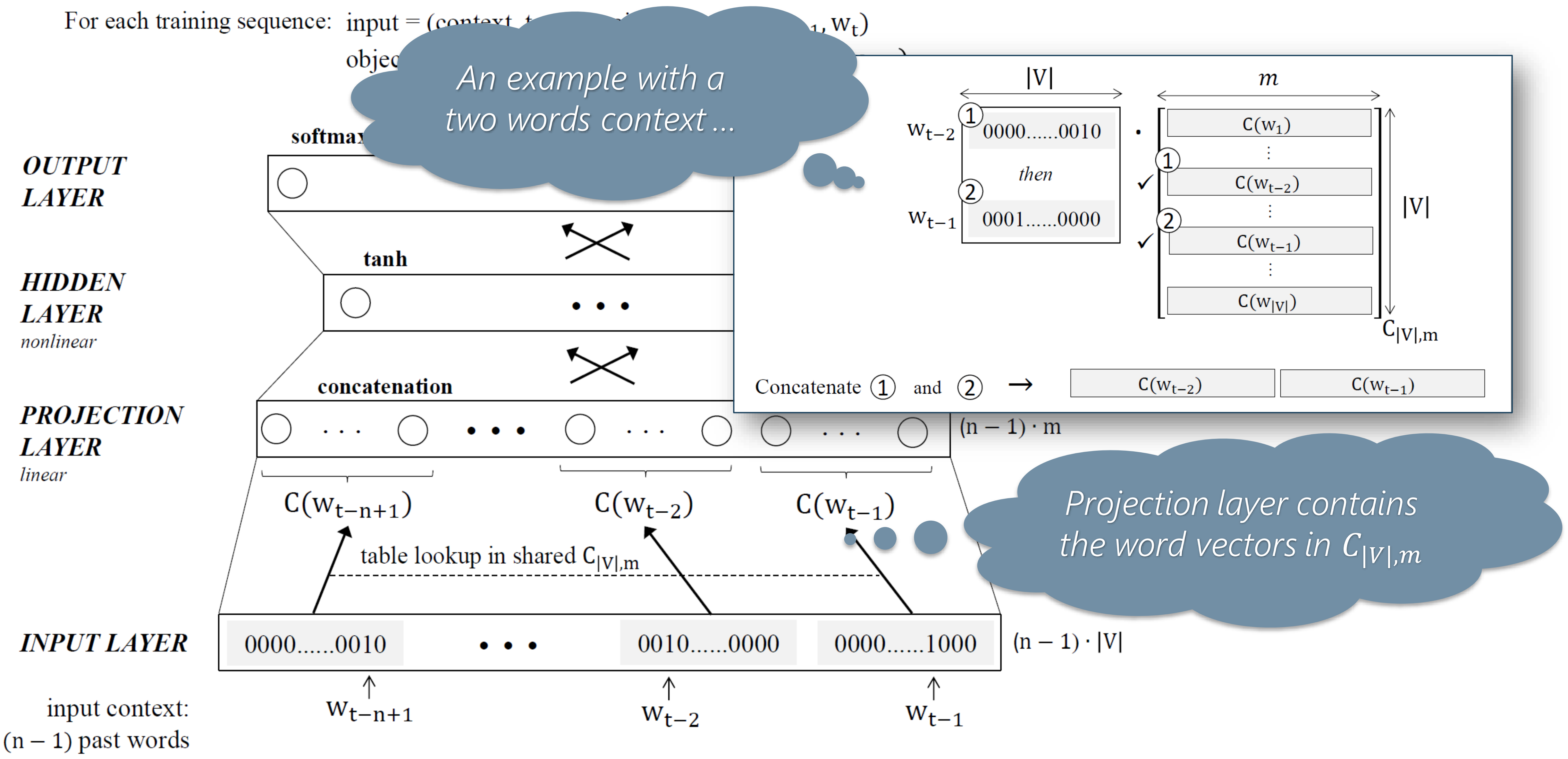

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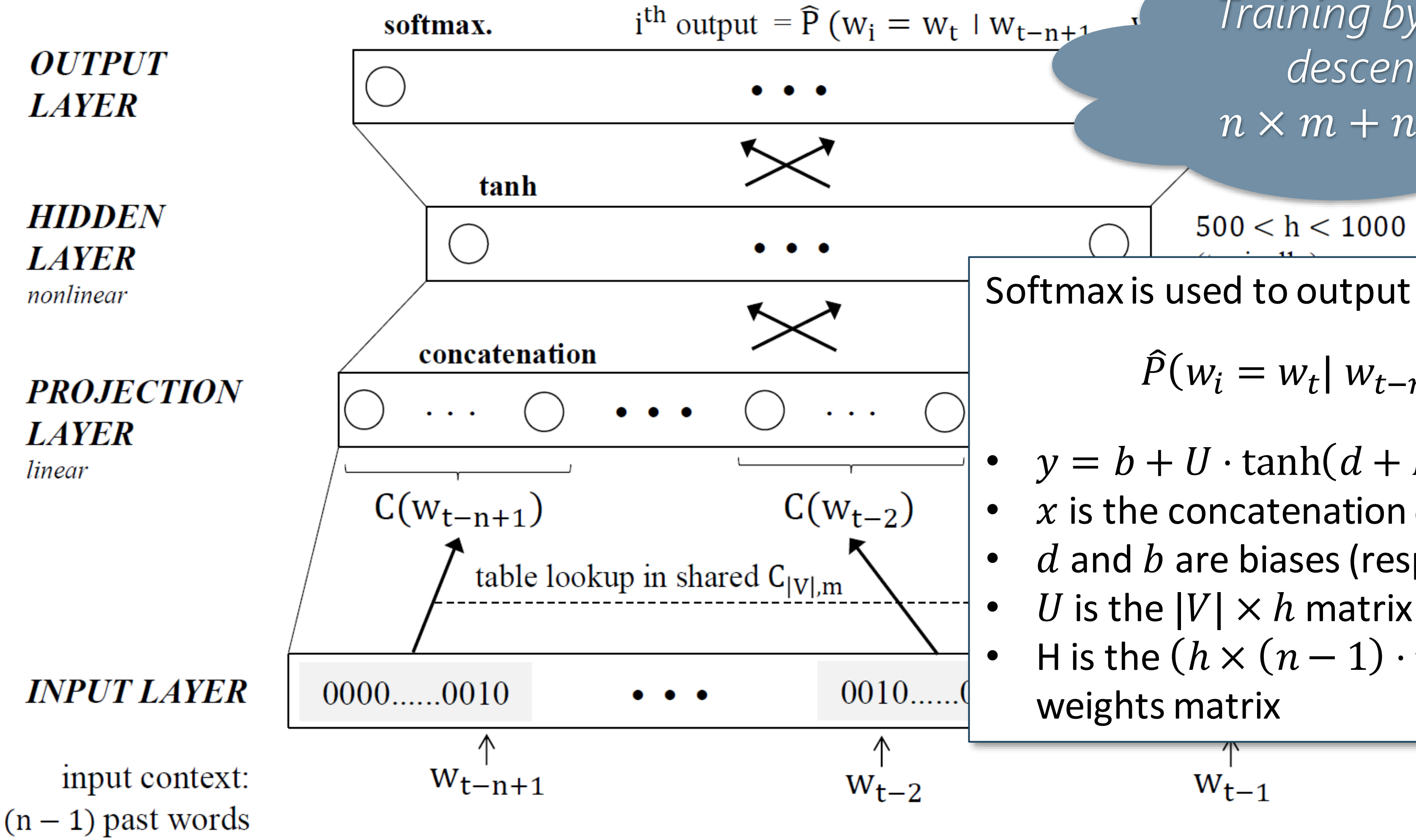

Training by stochastic gradient descent has complexity
$n \times m + n \times m \times h + \boldsymbol{h} \times |\boldsymbol{V}|$

Softmax is used to output a multinomial distribution

$$\hat{P}(w_i = w_t \mid w_{t-n+1}, \dots, w_{t-1}) = \frac{e^{y_{w_i}}}{\sum_{i'}^{|V|} e^{y_{w_{i'}}}}$$

- $y = b + U \cdot \tanh(d + H \cdot x)$
- x is the concatenation $C(w)$ of the context weight vectors
- d and b are biases (respectively h and $|V|$ elements)
- U is the $|V| \times h$ matrix with hidden-to-output weights
- H is the $(h \times (n-1) \cdot m)$ projection-to-hidden weights matrix

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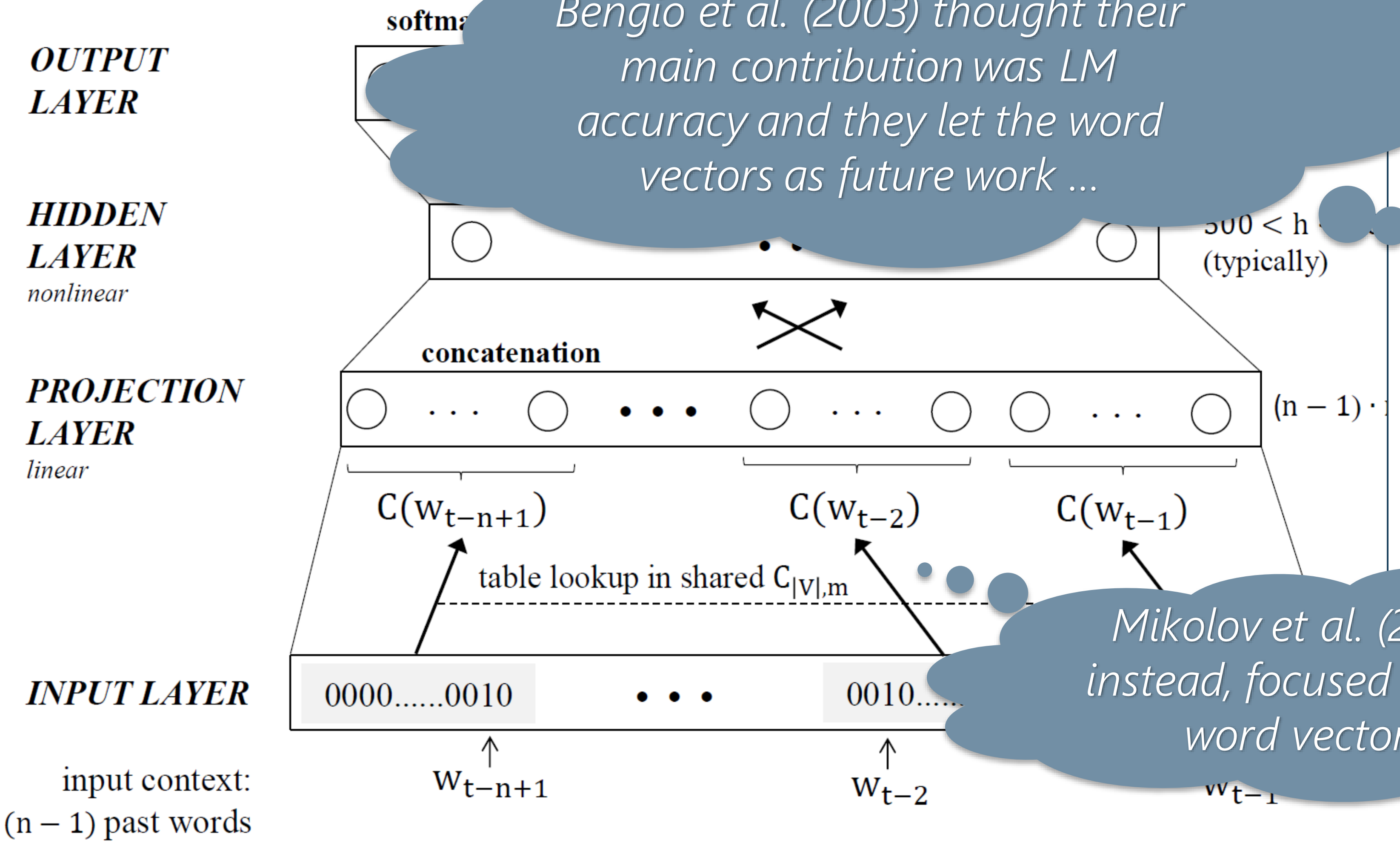


Bengio et al. (2003) thought their main contribution was LM accuracy and they let the word vectors as future work …

Mikolov et al. (2013), instead, focused on the word vectors

Tested on Brown (1.2M words, V≅ 16K, 200K test set) and AP News (14M words, V≅ 150K reduced to 18K, 1M est set)

- Brown: h=100, n=5, m=30
- AP News: h=60, n=6, m=100
- **3 week** training using **40 cores**
- 24% (Brown) and 8% (AP News) relative improvement wrt traditional smoothed n-gram in terms of test set perplexity

Due to **complexity**, NNLM can't be applied to large data sets and it shows … on rare words

Google's word2vec (Mikolov et al. 2013a)

<u>Idea</u>: achieve better performance allowing a simpler (shallower) model to be trained on much larger amounts of data

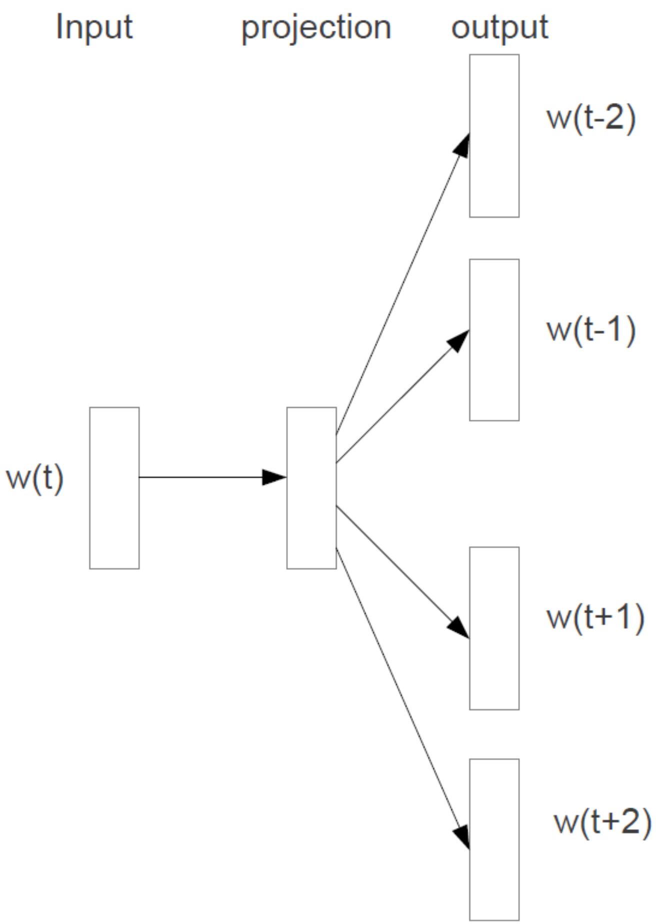
- No hidden layer (leads to 1000X speed up)
- Projection layer is shared (not just the weight m
- Context contain words both from history and futur

«You shall know a word by the company it keeps»
John R. Firth, 1957:11.

```
…Pelé has called Neymar an excellent player…
…At the age of just 22 years, Neymar had scored 40 goals in 58 internationals…
…occasionally as an attacking midfielder, Neymar was called a true phenomenon…
```

These words will represent **Neymar**

Google word2vec Flavors

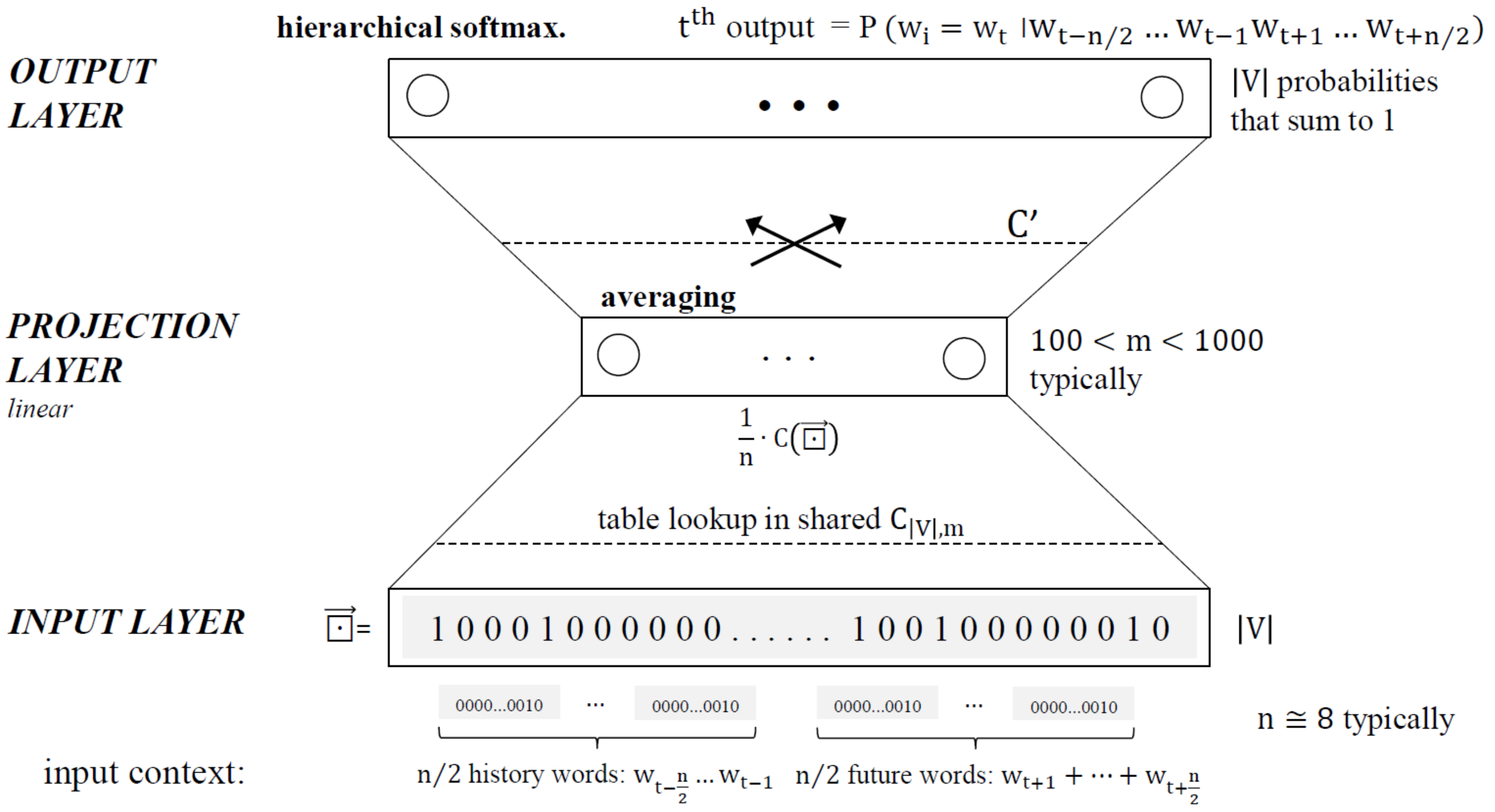


Skip-gram architecture

Word2vec's Continuous Bag-of-Words (CBOW)

For each training sequence: input = (context, target) pair: $(w_{t-\frac{n}{2}} \dots w_{t-1} w_{t+1} \dots w_{t+\frac{n}{2}}, w_t)$

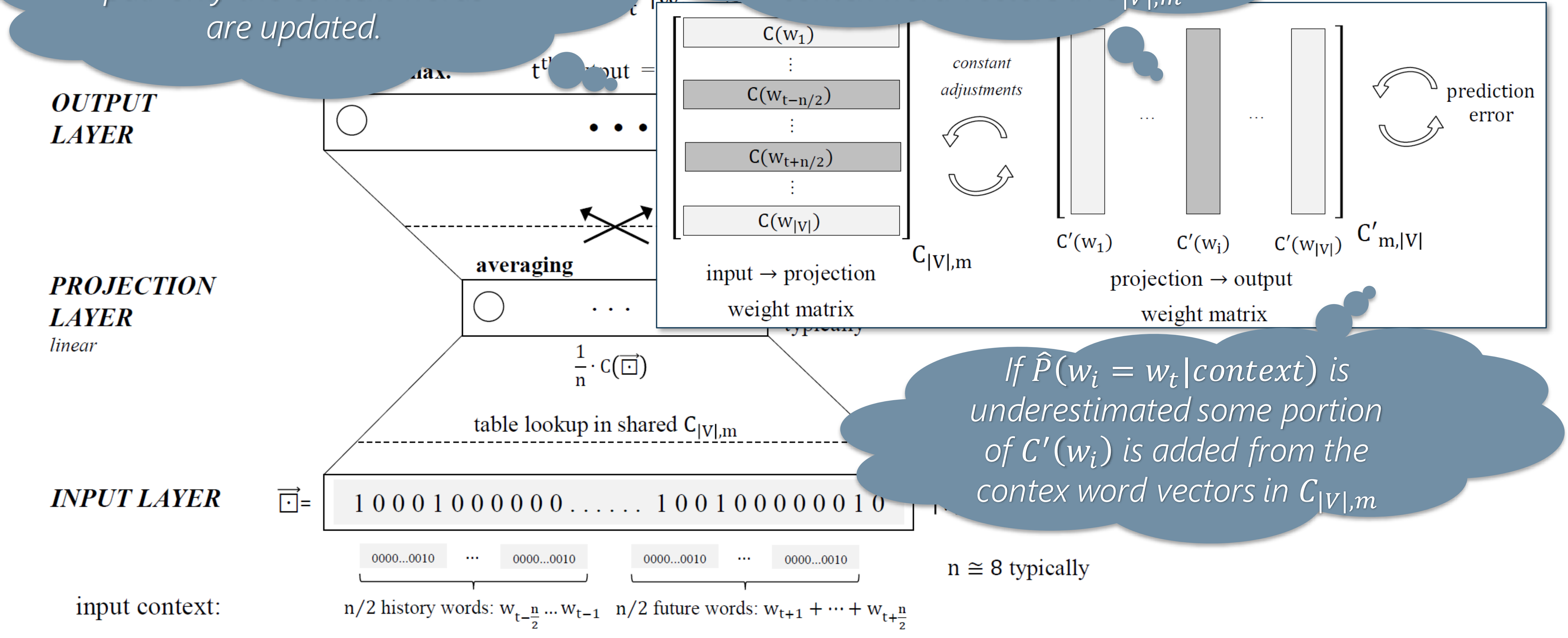
objective: minimize $E = -\log \hat{P}\left(w_t \mid w_{t-n/2} \dots w_{t-1} w_{t+1} \dots w_{t+n/2}\right)$



Word2vec's Continuous Bag-of-W

For each <context, target> pair only the context words are updated.

If $\hat{P}(w_i = w_t|context)$ is overestimated some portion of $C'(w_i)$ is subtracted from the contex word vectors in $C_{|V|,m}$



If $\hat{P}(w_i = w_t|context)$ is underestimated some portion of $C'(w_i)$ is added from the contex word vectors in $C_{|V|,m}$

Word2vec facts

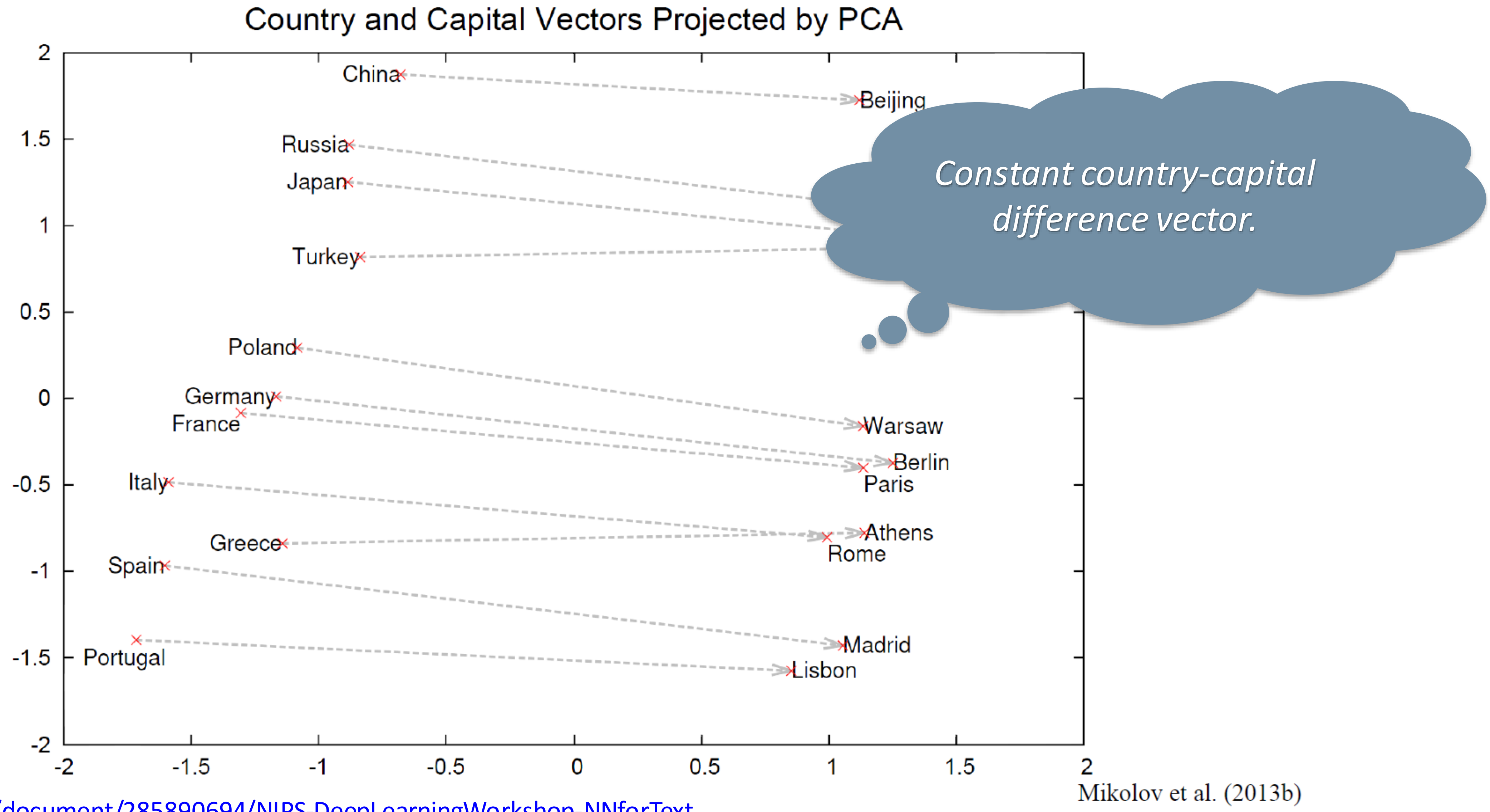
Word2vec shows significant improvements w.r.t. the NNML

- Complexity is $n \times m + m \times log|V|$ (Mikolov et al. 2013a)
- On Google news 6B words training corpus, with $|V| \sim 10^6$
  - CBOW with m=1000 took 2 days to train on 140 cores
  - Skip-gram with m=1000 took 2.5 days on 125 cores
  - NNLM (Bengio et al. 2003) took 14 days on 180 cores, for m=100 only!
- word2vec training speed ≅ 100K-5M words/s
- Best NNLM: 12.3% overall accuracy vs. Word2vec (with Skip-gram): 53.3%

Capital-Country	Past tense	Superlative	Male-Female	Opposite
Athens: **Greece**	walking: **walked**	easy: **easiest**	brother: **sister**	ethical: **unethical**

Adapted from Mikolov et al. (2013a)

Regularities in word2vec Embedding Space



Picture taken from:
https://www.scribd.com/document/285890694/NIPS-DeepLearningWorkshop-NNforText

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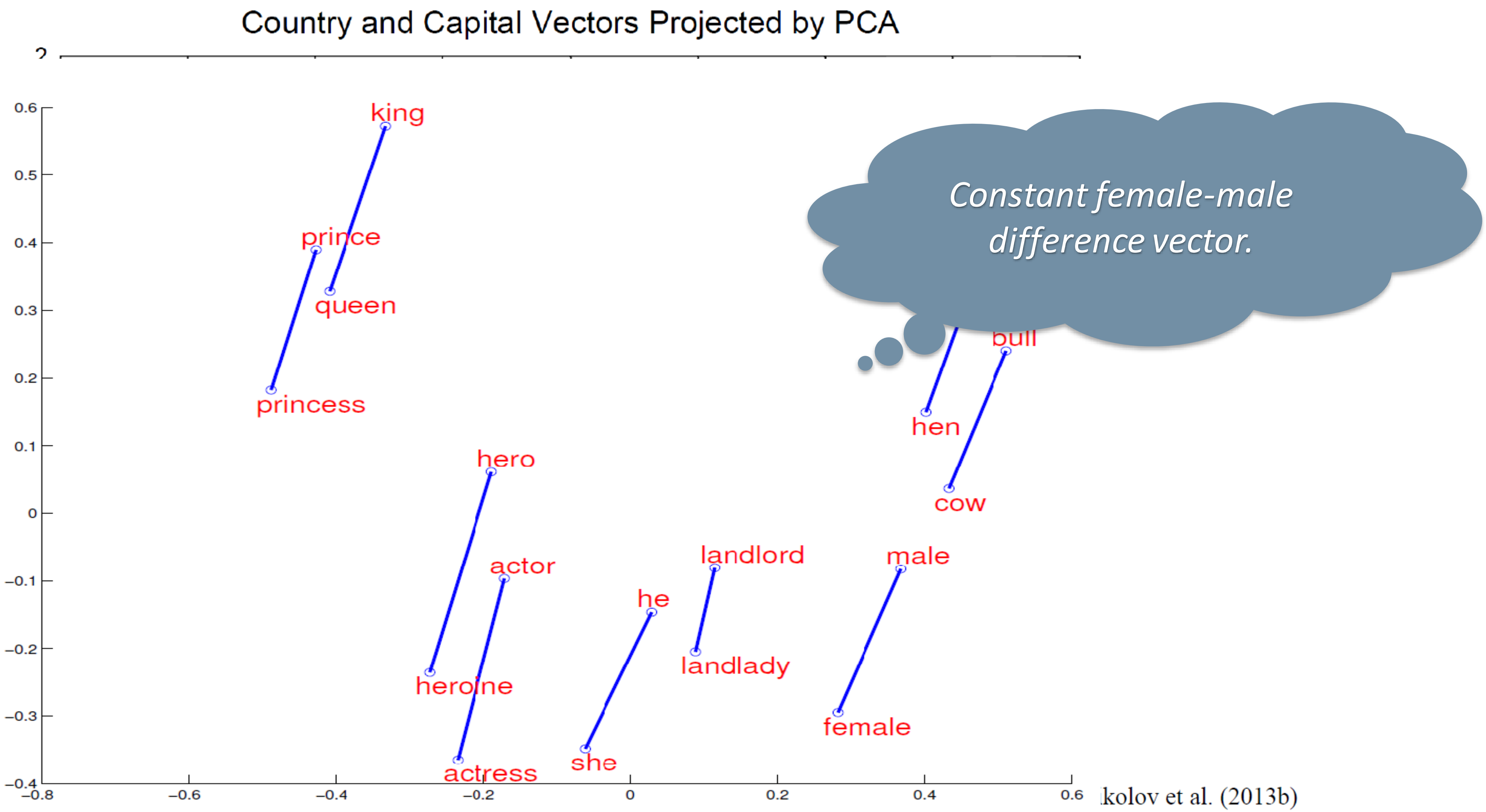

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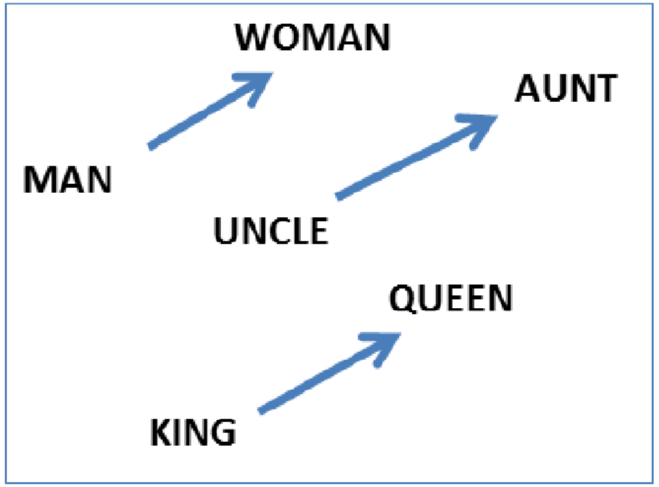
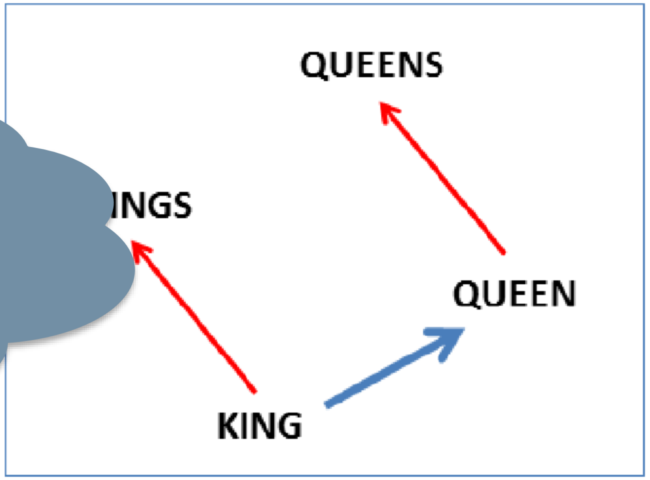
Regularities in word2vec Embedding Space

Vector operations are supported make «intuitive sense»:

- $w_{king} - w_{man} + w_{woman} \cong w_{queen}$
- $w_{paris} - w_{france} + w_{italy} \cong w_{rome}$
- $w_{windows} - w_{microsoft} + w_{google} \cong w_{android}$
- $w_{einstein} - w_{scientist} + w_{painter} \cong w_{picasso}$
- $w_{his} - w_{he} + w_{she} \cong w_{her}$
- $w_{cu} - w_{copper} + w_{gold} \cong w_{au}$
- …





«You shall know a word by the company it keeps»
John R. Firth, 1957:11.

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Applications of word2vec in Information Retrieval

Query: “restaurants in mountain view that are not very good”

Phrases: “restaurants in (mountain view) that are (not very good)”

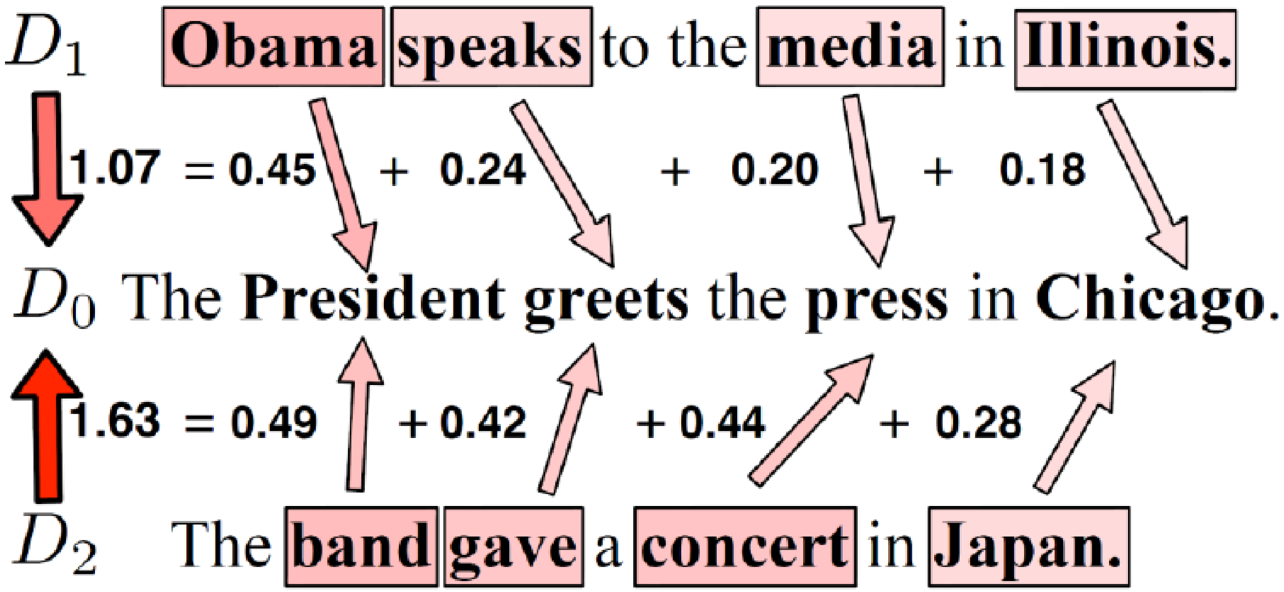
Vectors: “restaurants+in+(mountain view)+that+are+(not very good)”

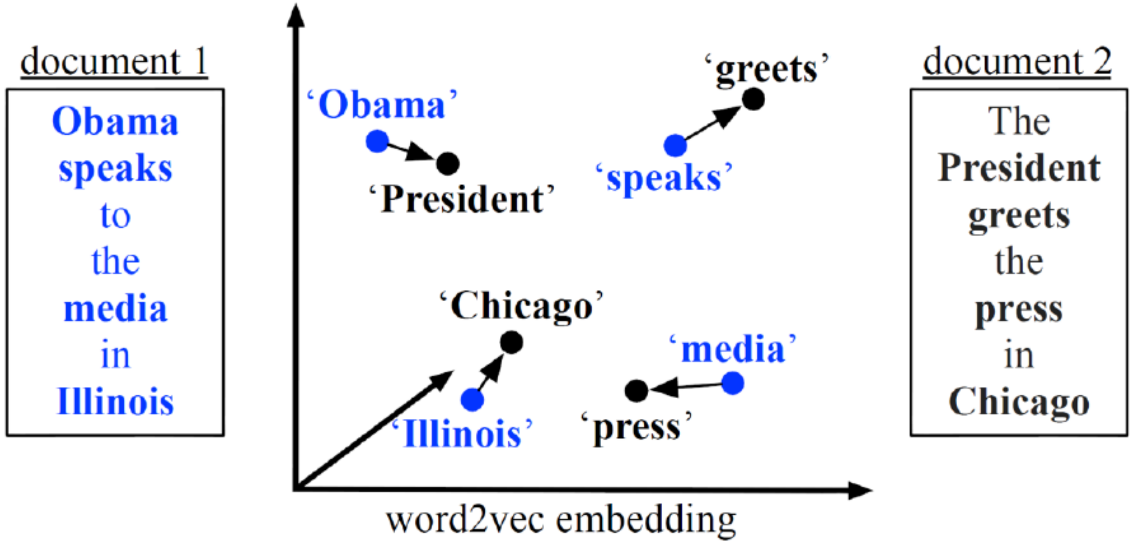
Expression	*Nearest tokens*
Czech + currency	koruna, Czech crown, Polish zloty, CTK
Vietnam + capital	Hanoi, Ho Chi Minh City, Viet Nam, Vietnamese
German + airlines	airline Lufthansa, carrier Lufthansa, flag carrier Lufthansa
Russian + river	Moscow, Volga River, upriver, Russia
French + actress	Juliette Binoche, Vanessa Paradis, Charlotte Gainsbourg

(Simple and efficient, but will not work for long sentences or documents)

Applications of word2vec in Document Classification/Similarity

With BoW D_1 and D_2 are equally similar to D_0.





Word embeddings allow to capture the «semantics» of the document …

Applications of word2vec in Sentiment Analysis

No need for classifiers, just use cosine distanc

«You shall know a word by the company it keeps»
John R. Firth, 1957:11.

```
Enter word or sentence (EXIT to break): sad

Word: sad  Position in vocabulary: 4067

                                          Word       Cosine distance
------------------------------------------------------------------------
                                    saddening               0.727309
                                          Sad               0.661083
                                     saddened               0.660439
                                 heartbreaking              0.657351
                                  disheartening             0.650732
                                 Meny_Friedman              0.648706
                       parishioner_Pat_Patello              0.647586
                                    saddens_me              0.640712
                                   distressing              0.639909
                             reminders_bobbing              0.635772
                              Turkoman_Shiites              0.635577
                                      saddest               0.634551
                                   unfortunate              0.627209
                                        sorry               0.619405
                                   bittersweet              0.617521
                                        tragic              0.611279
                                    regretful               0.603472
```

GloVe: Global Vectors for Word Representation (Pennington et al. 2014)

GloVe makes explicit what word2vec does implicitly

- Encodes meaning as vector offsets in an embedding space
- Meaning is encoded by ratios of co-occurrece probabilities

Probability and Ratio	$k = solid$	$k = gas$	$k = water$	$k = fashion$
$P(k\|ice)$	1.9×10^{-4}	6.6×10^{-5}	3.0×10^{-3}	1.7×10^{-5}
$P(k\|steam)$	2.2×10^{-5}	7.8×10^{-4}	2.2×10^{-3}	[illegible]
$P(k\|ice)/P(k\|steam)$	8.9	8.5×10^{-2}	[illegible]	[illegible]

Refer to Pennington et al. paper for details on this loss function …

Trained by weighted least squares

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$$

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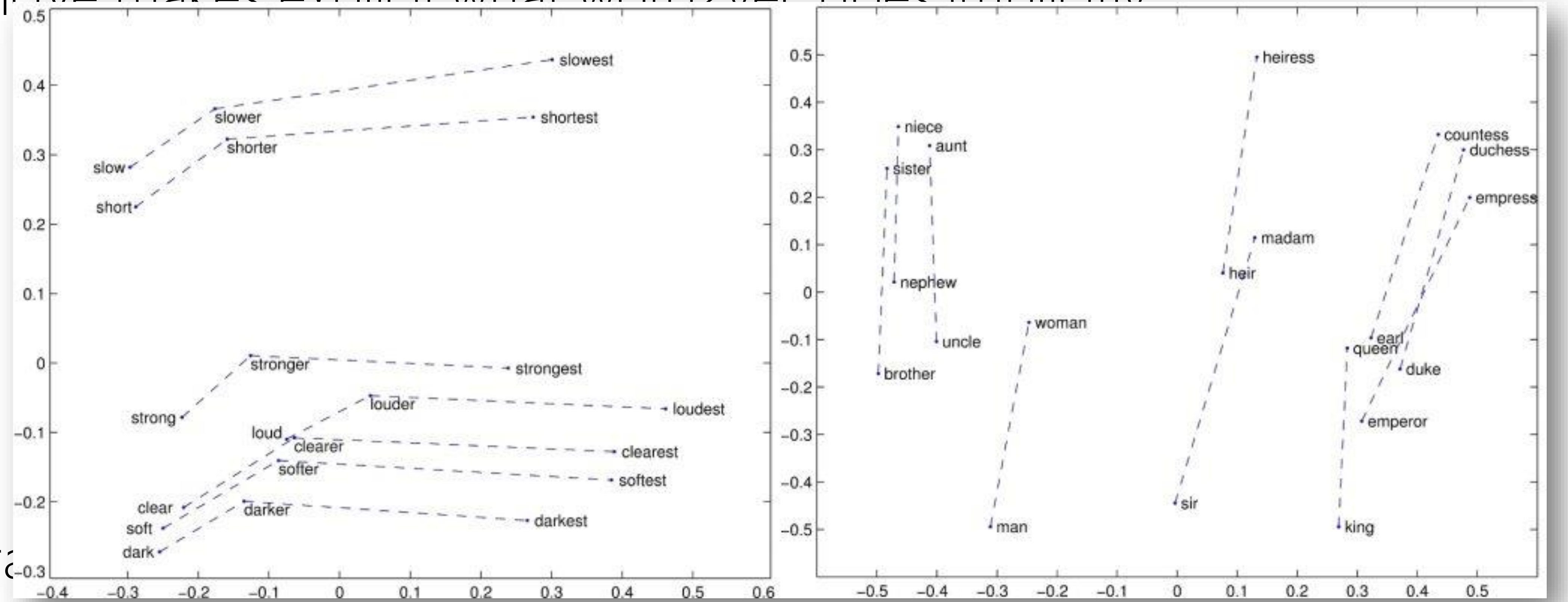

Tr

$$J = \sum_{i,j=1}^{V} f\left(X_{ij}\right)\left(w_i^T \tilde{w}_j + b_i + \tilde{b}_j - \log X_{ij}\right)^2$$

Nearest Neighbours with GloVe

What are the closest words to the target word *frog*:

1. *Frog*
2. Frogs
3. Toad
4. Litoria
5. Leptodactylidae
6. Rana
7. Lizard
8. Eleutherodactylus

3. litoria

4. leptodactylidae

5. rana

7. eleutherodactylus