POLITÉCNICA
"Ingeniamos el futuro"
CAMPUS
DE EXCELENCIA
INTERNACIONAL

Text Mining 3 Representation Learning

Madrid Summer School on
Advanced Statistics and Data Mining

Florian Leitner
Data Catalytics, S.L.
leitner@datacatytics.com

Representation learning

- a **transformation of raw data** to a representation that can be effectively exploited in machine learning tasks
- **obviates feature engineering** (manually developing a representation to use for the classifier)
- many feature learning techniques do not required labeled data (i.e., are fully **unsupervised**)

Word representations

A trivial approach is to use a token's string itself as the representation; Numerically encode that leads us to a sparse, **one-hot** vector:

$$\text{"}\textit{tutorial}\text{"} := [0\ 0\ 0\ 0\ \ldots\ 0\ 0\ 0\ 0\ \mathbf{1}\ 0\ 0\ 0\ 0\ \ldots\ 0\ 0\ 0]$$

Problem: every such vector v is orthogonal to all others, so:

$$\mathbf{v}_1^{\mathrm{T}} \cdot \mathbf{v}_2 = \mathbf{0}$$

In other words, there is no notion of similarity between those vectors.

Therefore, the goal of word representations is to [numerically] **quantify the similarity of related words**.

From one-hot encoding to word embeddings

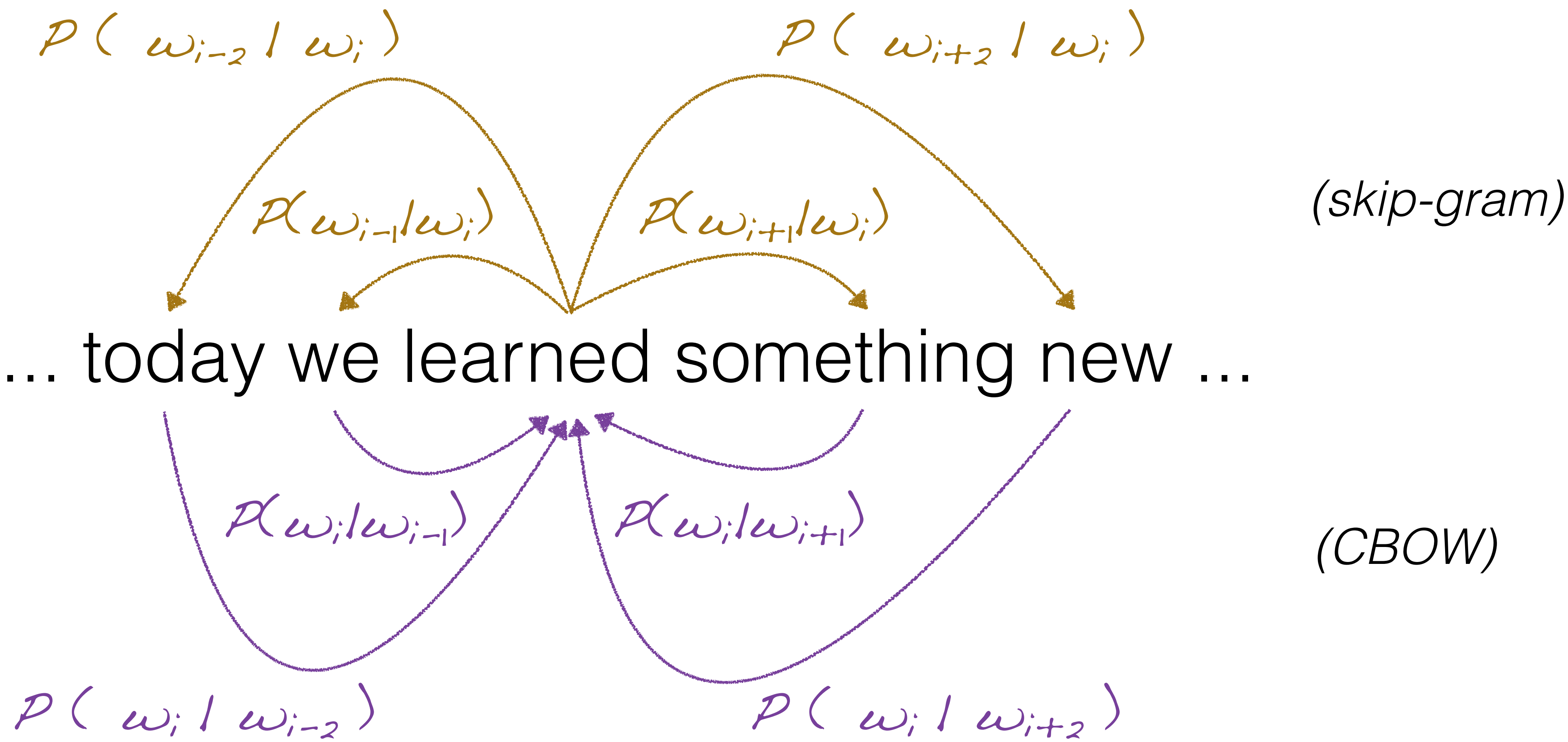
```
fun   = [1.0, 0.0, …, 0.0, 0.0, …, 0.0]
enjoy = [0.0, 0.0, …, 1.0, 0.0, …, 0.0]
like  = [0.0, 0.0, …, 0.0, 0.0, …, 1.0]
```

```
fun   = [0.6, 0.0, …, 0.3, 0.0, …, 0.1]
enjoy = [0.4, 0.0, …, 0.5, 0.0, …, 0.1]
like  = [0.2, 0.0, …, 0.2, 0.0, …, 0.6]
```

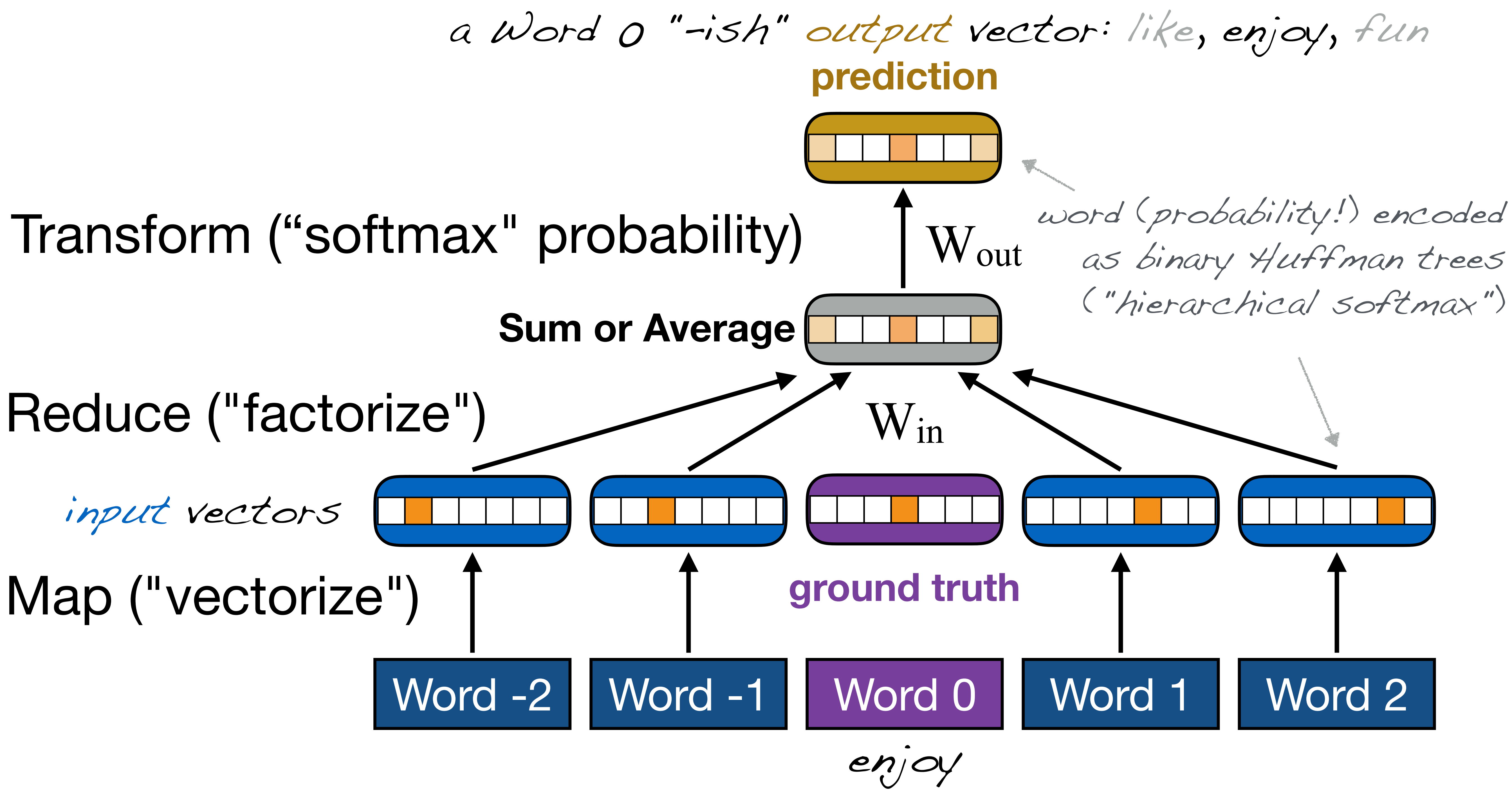
"You shall know a word by the company it keeps"

- J. R. Firth, **1957**:11
  (so the idea of word embeddings is definitely not new...)
- That is, the **context** (the surrounding words) of a word is dependent on the word itself; Put it slightly differently: a word "dictates" the possible words you can find in its surrounding.

Predicting the surrounding of words (and vice versa)



Word embeddings with neural networks (CBOW model)



Where are the final word embeddings (vectors)?

Embeddings := $\| W_{in} \|_2$

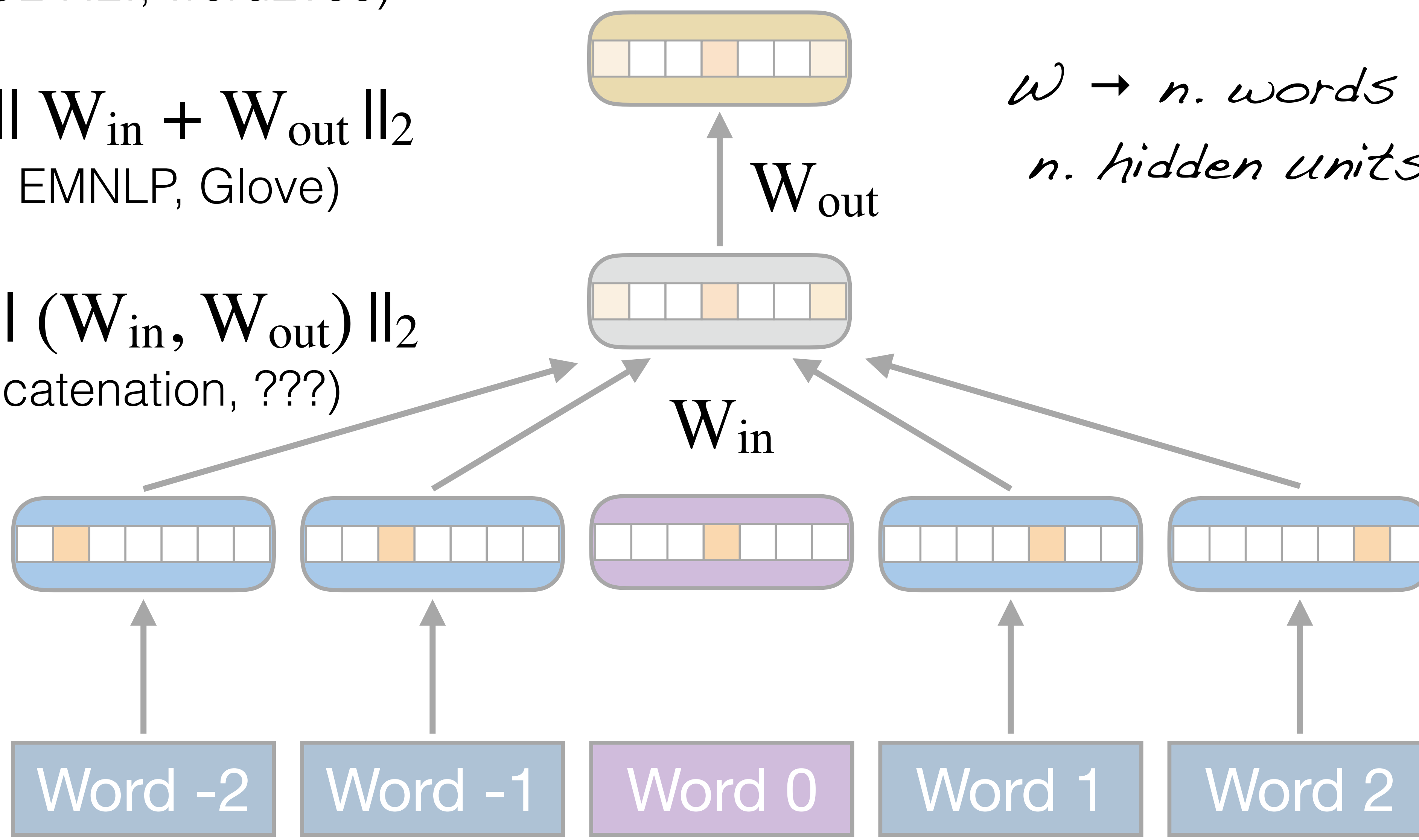
(Mikolov 2013, NAACL-HLT, word2vec)

Embeddings := $\| W_{in} + W_{out} \|_2$

(Pennington 2014, EMNLP, Glove)

Embeddings := $\| (W_{in}, W_{out}) \|_2$

(in+out vector concatenation, ???)

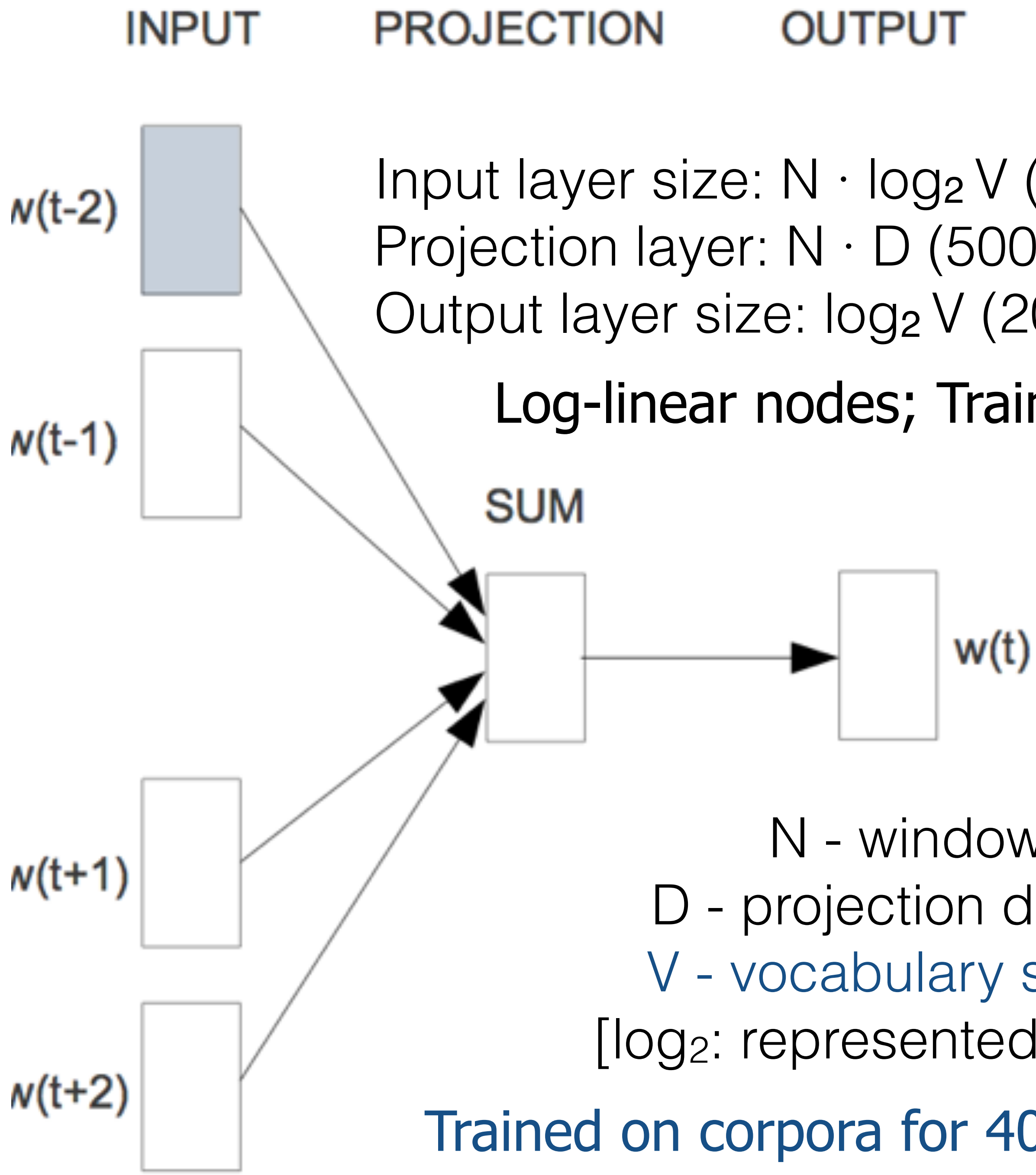


$W \rightarrow$ n. words × n. hidden units

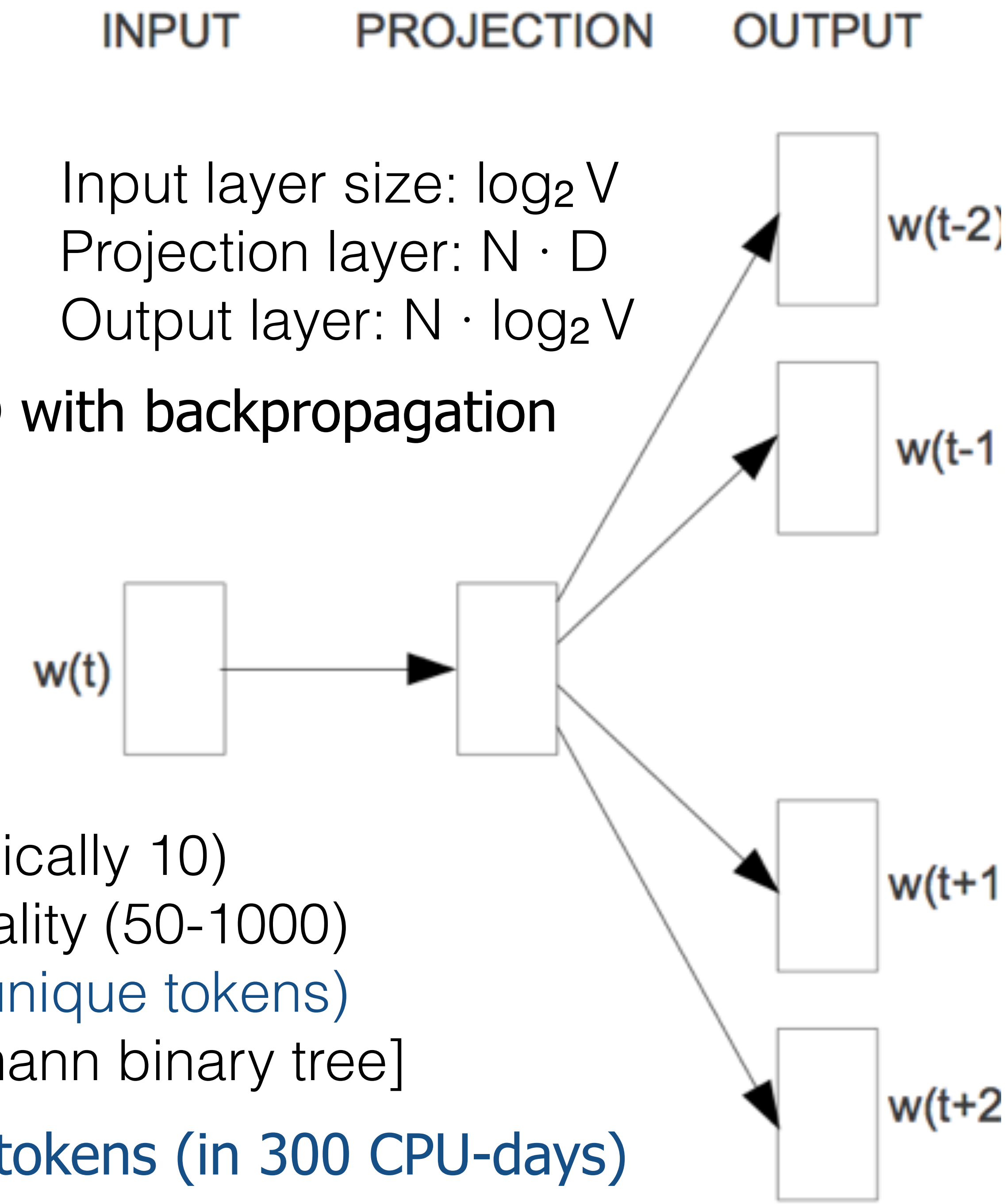
NB: softmax CBOW is easier to understand, but skip-gram with negative subsampling (SGNS) performs better

Neural network models of language

word2vec - Thomas Mikolov et al. - Google - 2013



Input layer size: $N \cdot \log_2 V$ (200)
Projection layer: $N \cdot D$ (500-20k)
Output layer size: $\log_2 V$ (20)



Input layer size: $\log_2 V$
Projection layer: $N \cdot D$
Output layer: $N \cdot \log_2 V$

Log-linear nodes; Training: SGD with backpropagation

N - window size (typically 10)
D - projection dimensionality (50-1000)
V - vocabulary size (**1M** unique tokens)
[$\log_2$: represented as Huffmann binary tree]

Trained on corpora for 40M to **6B** tokens (in 300 CPU-days)

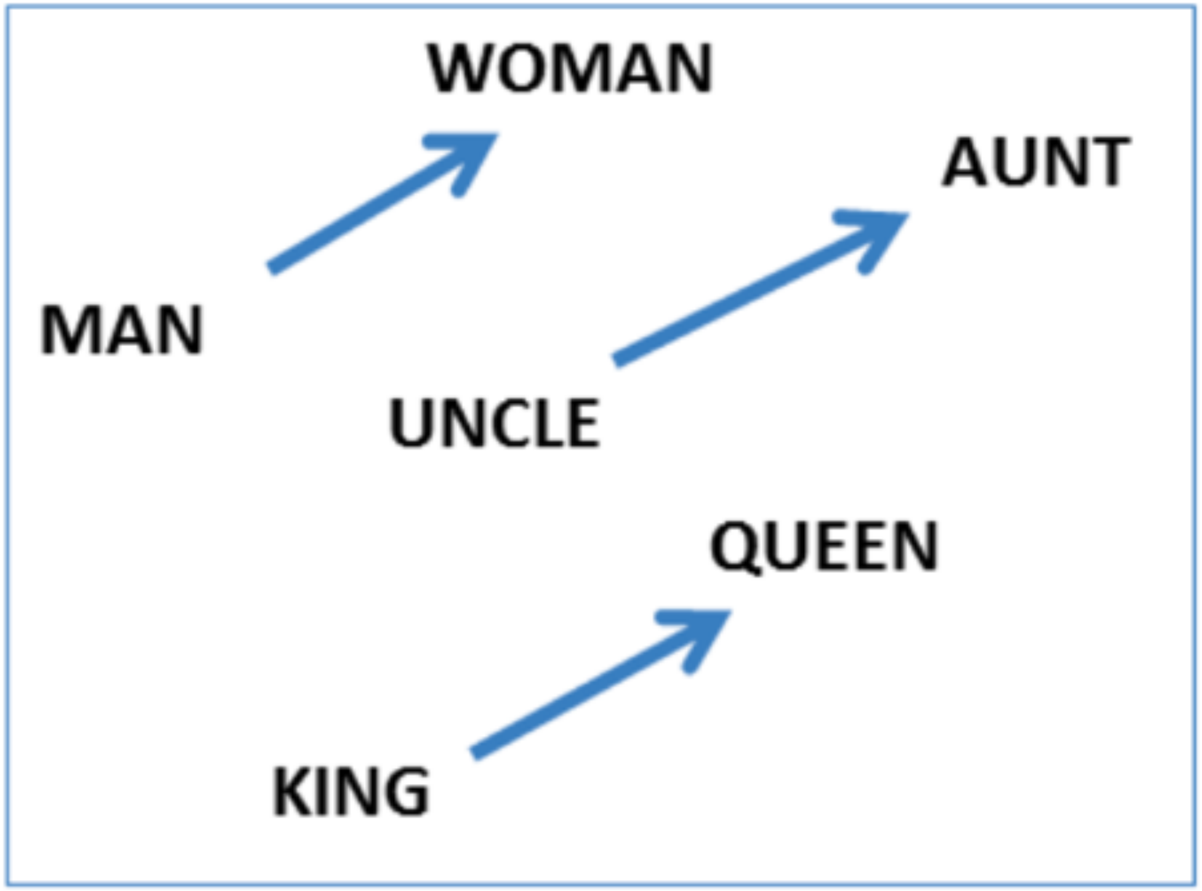
CBOW

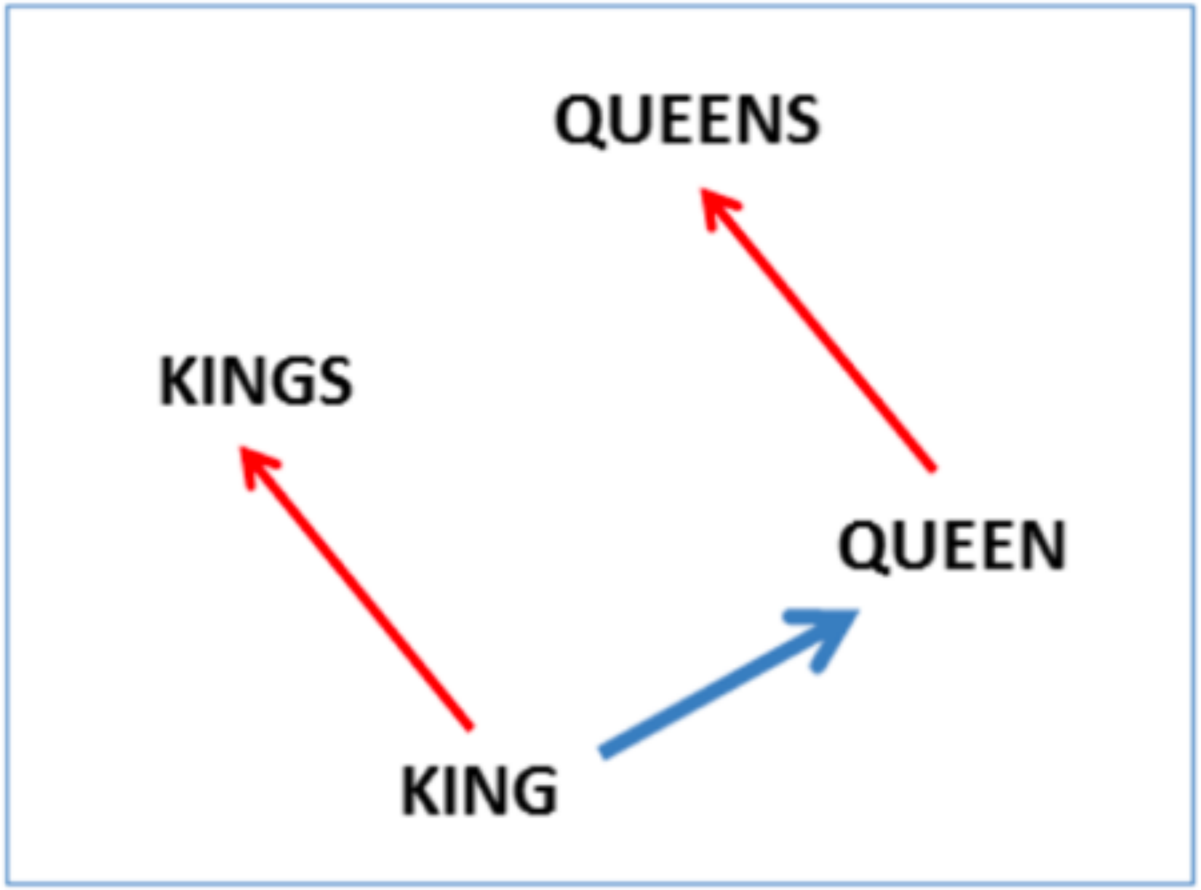
predict a word from its surrounding

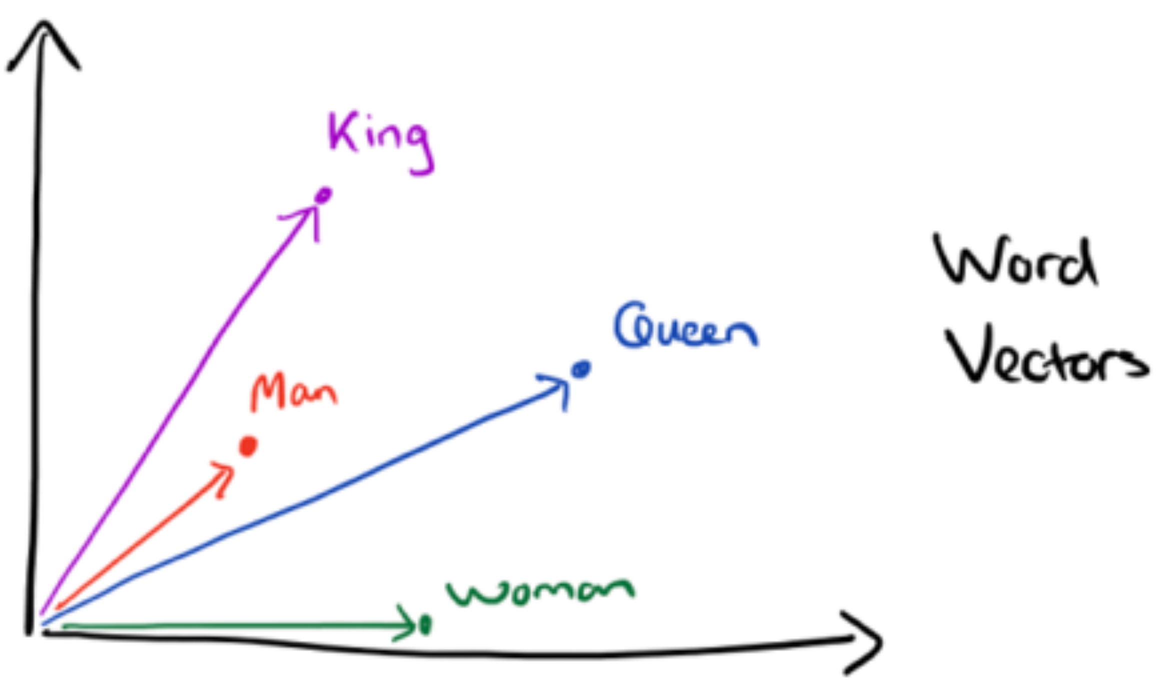
Skip-gram

predict the surrounding of a word

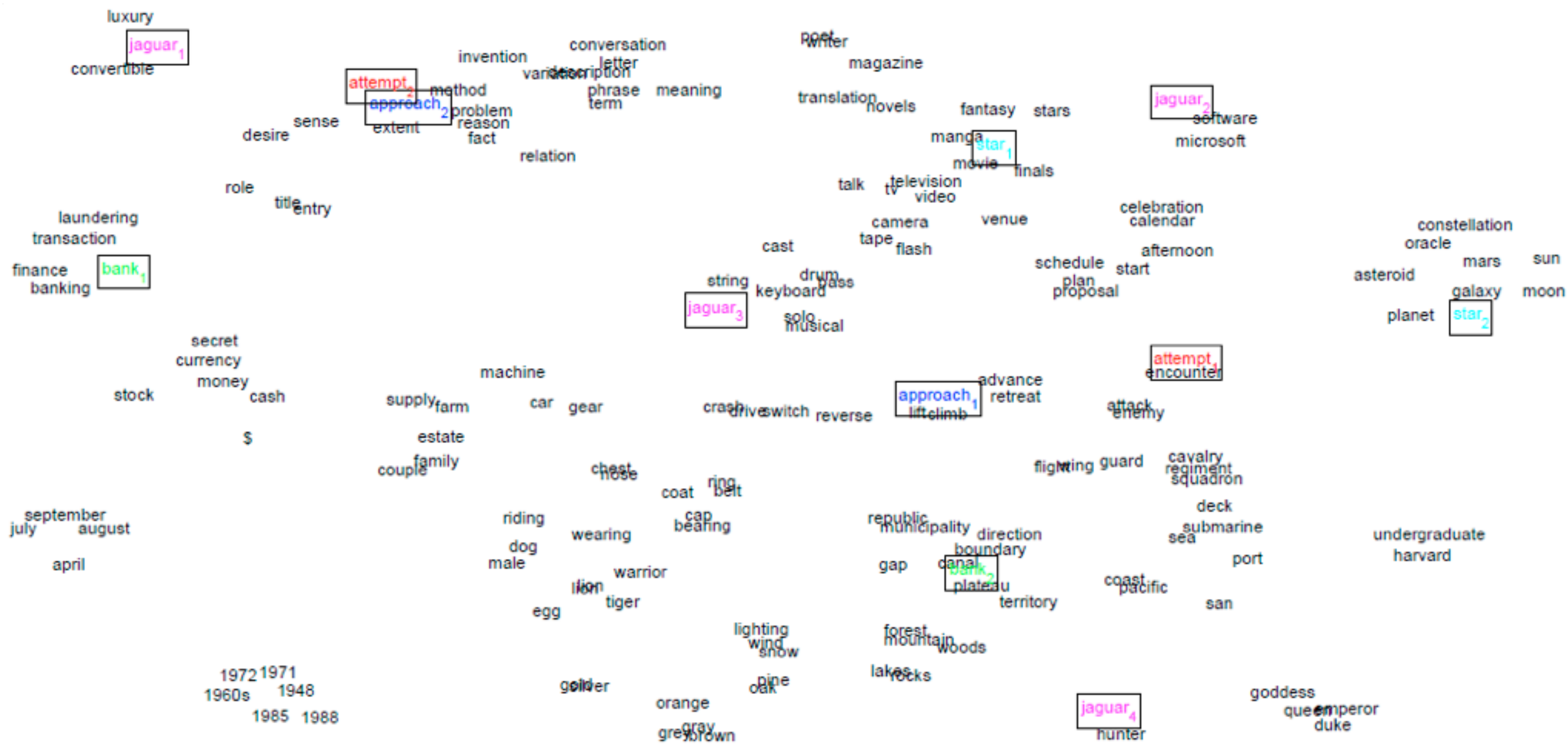
King - Man + Woman = ?







word2vec: co-occurrence probs.
GloVe: ratio of co-occ. probabilities

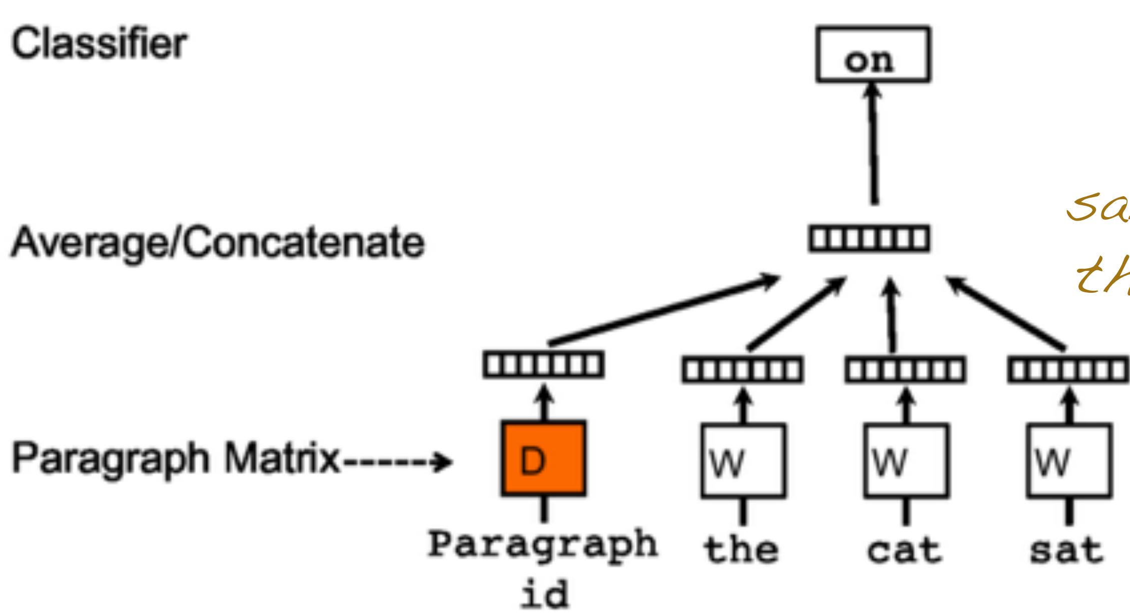


Mikolov, T., Chen, K., Corrado, G., & Dean, J. (2013). Efficient Estimation of Word Representations in Vector Space. ICLR Workshop.

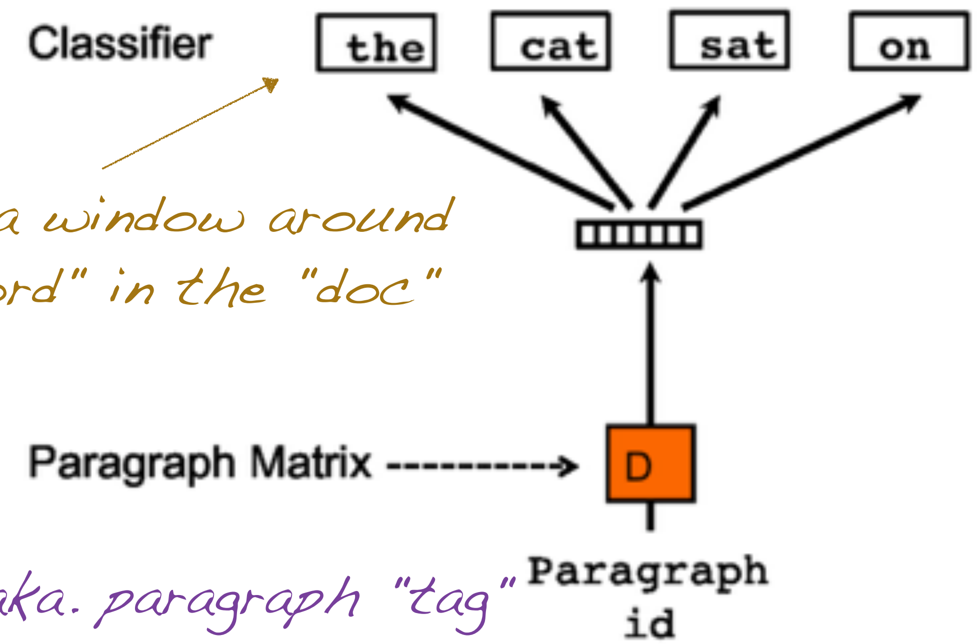
Pennington, J., Socher, R., & Manning, C. D. (2014). Glove: Global vectors for word representation. In Proceedings of the Empiricial Methods in Natural Language Processing (pp. 1532–1543).

Text embeddings with Paragraph Vectors (doc2vec)

a "doc" is some piece of text: a sentence, a tweet, a paragraph, or even a whole document



sampled from a window around the "target word" in the "doc"



aka. paragraph "tag"

PV-Distributed Memory (DM)
Predict the target word from the paragraph vector and the doc's words (from a window over the doc centered at the target word).

Distributed BOW-PV
Predict the doc's words (from some window over the doc) from the paragraph vector.

Le's & Mikolov's recommendation: train both models (using concatenation) and combine them.

Le, Q., and Mikolov, T. (2014). Distributed Representations of Sentences and Documents. 2014

Paragraph vectors (doc2vec)

- Base idea is the same as word embeddings
  - c.f. CBOW/SGNS models
- But the **paragraph vector** D **needs to be inferred** when using this model ("in production")
  - i.e., you **predict** the embedding
  - c.f. **looking up** the embedding vector for words
- D is a **tag** for each doc
  - used as memory for that doc during training
  - typically just a unique integer per doc

Out-of-vocabulary (OOV) words: character n-grams

Problem: no embedding for words not seen during training

Solution: instead learn the embeddings of a word's n-grams

split each word into its **character** n-grams (typically, $n = [3, 6]$; and just use the word "as is" for tokens with character lengths < 4)

learn to embed the n-grams, with the target embedding being the average over the predicted n-gram embeddings

fastText: Joulin et al., 2016, arXiv (Facebook)

Cheap Solution: bucket all words into a fixed-size hash-table (smaller than the actual vocabulary) and allow for collisions (also known as the "**hashing trick**")

Statistical models of language and polysemy

- Polysemous words have multiple meanings (e.g., “bank”).
  - This is a real problem in scientific texts because polysemy is frequent.
- One idea: Create **context vectors** for each sense of a word (vector).
  - MSSG - Neelakantan et al. - 2015
- Caveat: Performance isn’t much better than for the skip-gram model by Mikolov et al., while training is ~5x slower.
- Simpler approach (partial solution only): use collocations
  - Either train the embeddings over the merged collocations (tomorrow's lesson), or [also] use bigrams as your embedding inputs (vs. of the [unigram] tokens)

Word embeddings: Applications in TM & NLP

- Opinion mining (Maas et al., 2011)
- Paraphrase detection (Socher et al., 2011)
- Chunking (Turian et al., 2010; Dhillon and Ungar, 2011)
- Named entity recognition (Neelakantan and Collins, 2014; Passos et al., 2014; Turian et al., 2010)
- Dependency parsing (Bansal et al., 2014)