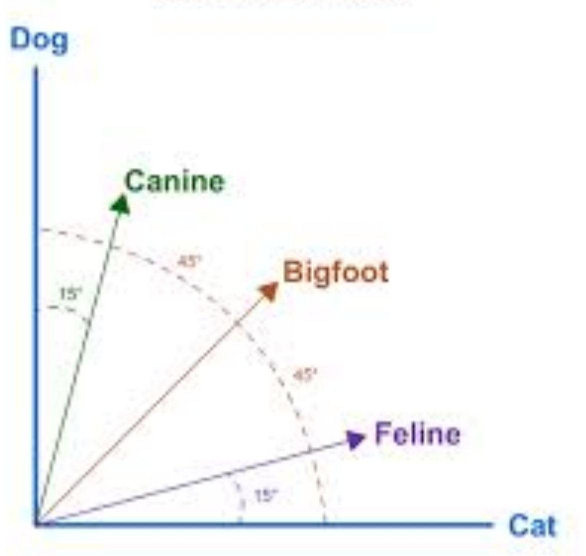
Distributional Semantics

COMP90042 Lecture 10



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Lexical databases - Problems

- Manually constructed
  - Expensive
  - Human annotation can be biased and noisy
- Language is dynamic
  - New words: slang, terminology, etc.
  - New senses
- The Internet provides us with massive amounts of text. Can we use that to obtain word meanings?

Distributional semantics

- “You shall know a word by the company it keeps” (Firth)
- Document co-occurrence often indicative of topic (*document* as context)
  - E.g. *voting* and *politics*
- Local context reflects a word’s semantic class (*word window* as context)
  - E.g. *eat a pizza, eat a burger*
- Two approaches:
  - Count-based (Vector Space Models)
  - Prediction-based

The Vector space model

- Fundamental idea: represent meaning as a vector
- Consider documents as context (ex: tweets)
- One matrix, two viewpoints
  - Documents represented by their words (web search)
  - Words represented by their documents (text analysis)

	…	state	fun	heaven	…
…					
425		0	1	0	
426		3	0	0	
427		0	0	0	
……					

Manipulating the VSM

- Weighting the values
- Creating low-dimensional dense vectors
- Comparing vectors

Tf-idf

- Standard weighting scheme for information retrieval
- Also discounts common words

$$idf_w = \log \frac{|D|}{df_w}$$

	…	the	country	hell	…
…					
425		43	5	1	
426		24	1	0	
427		37	0	3	
…					
df		500	14	7	

tf matrix

	…	the	country	hell	…
…					
425		0	25.8	6.2	
426		0	5.2	0	
427		0	0	18.5	
…					

tf-idf matrix

Dimensionality reduction

- Term-document matrices are very *sparse*
- Dimensionality reduction: create shorter, denser vectors
- More practical (less features)
- Remove noise (less overfitting)

Singular value Decomposition

$$A = U\Sigma V^T$$

$$\begin{array}{cc} & |D| \\ |V| & \begin{bmatrix} 0 & 1 & 0 & & 0 \\ 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0 \end{bmatrix} \end{array}$$

A
(term-document matrix)

m=$Rank(A)$

U
(new term matrix)

$$\begin{array}{cc} & m \\ |V| & \begin{bmatrix} 2.2 & 0.3 & & 8.7 \\ 5.5 & -2.8 & \cdots & 0.1 \\ -1.3 & 3.7 & & 3.5 \\ \vdots & & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -1.9 \end{bmatrix} \end{array}$$

Σ
(singular values)

$$\begin{array}{cc} & m \\ m & \begin{bmatrix} 9.1 & 0 & 0 & & 0 \\ 0 & 4.4 & 0 & \cdots & 0 \\ 0 & 0 & 2.3 & & 0 \\ & \vdots & & \ddots & \vdots \\ 0 & 0 & 0 & \cdots & 0.1 \end{bmatrix} \end{array}$$

V^T
(new document matrix)

$$\begin{array}{cc} & |D| \\ m & \begin{bmatrix} -0.2 & 4.0 & & -1.3 \\ -4.1 & 0.6 & \cdots & -0.2 \\ 2.6 & 6.1 & & 1.4 \\ \vdots & & \ddots & \vdots \\ -1.9 & -1.8 & \cdots & 0.3 \end{bmatrix} \end{array}$$

Truncating – latent semantic analysis

- Truncating *U, Σ,* and *V* to *k* dimensions produces best possible *k* rank approximation of original matrix
- So truncated, U_k (or V_k^T) is a new low dimensional representation of the word (or document)
- Typical values for *k* are 100-5000

$$U \qquad \begin{array}{c} \\ |V| \end{array} \begin{array}{c} \begin{array}{cc} m & \vert\; k \end{array} \\ \begin{bmatrix} 2.2 & 0.3 & & -2.4 & & 8.7 \\ 5.5 & -2.8 & \cdots & 1.1 & \cdots & 0.1 \\ -1.3 & 3.7 & & 4.7 & & 3.5 \\ & \vdots & \ddots & \vdots & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -3.3 & \cdots & -1.9 \end{bmatrix} \end{array} \Rightarrow \quad U_k \quad \begin{array}{c} \\ |V| \end{array} \begin{array}{c} k \\ \begin{bmatrix} 2.2 & 0.3 & & -2.4 \\ 5.5 & -2.8 & \cdots & 1.1 \\ -1.3 & 3.7 & & 4.7 \\ \vdots & & \ddots & \vdots \\ 2.9 & -2.1 & \cdots & -3.3 \end{bmatrix} \end{array}$$

Words as context

- Lists how often words appear with other words
  - In some predefined context (usually a window)
- The obvious problem with raw frequency: dominated by common words

	…	the	country	hell	…
…					
state		1973	10	1	
fun		54	2	0	
heaven		55	1	3	
……					

Pointwise mutual information

For two events *x* and *y*, pointwise mutual information (PMI) comparison between the actual joint probability of the two events (as seen in the data) with the expected probability under the assumption of independence

$$PMI(x, y) = \log_2 \frac{p(x, y)}{p(x)p(y)}$$

Calculating PMI

	…	the	countr y	hell	…		Σ
…							
state		1973	10	1			12786
fun		54	2	0			633
heaven		55	1	3			627
…							
Σ		1047519	3617	780			15871304

$p(x,y) = \text{count}(x,y)/\Sigma$

$p(x) = \Sigma_x / \Sigma$

$p(y) = \Sigma_y / \Sigma$

x= state, y = country

$p(x,y) = 10/15871304 = 6.3 \text{ x } 10^{-7}$

$p(x) = 12786/15871304 = 8.0 \text{ x } 10^{-4}$

$p(y) = 3617/15871304 = 2.3 \text{ x } 10^{-4}$

$PMI(x,y) = \log_2(6.3 \text{ x } 10^{-7})/((8.0 \text{ x } 10^{-4})\ (2.3 \text{ x } 10^{-4}))$

$= 1.78$

PMI matrix

- PMI does a better job of capturing interesting semantics
  - E.g. *heaven* and *hell*
- But it is obviously biased towards rare words
- And doesn't handle zeros well

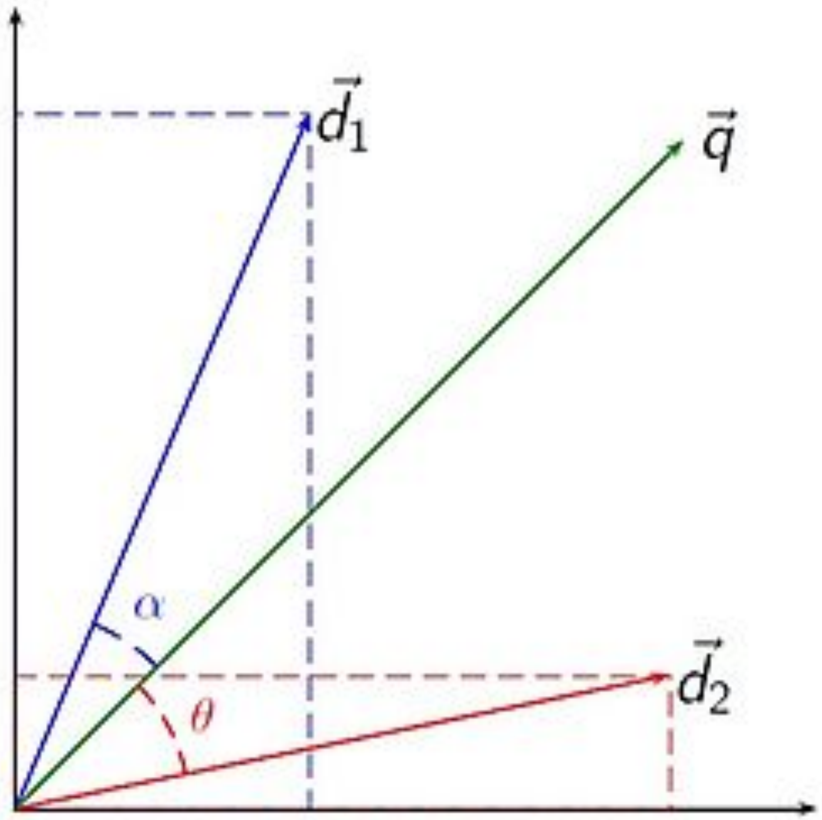
	…	the	country	hell	…
…					
state		1.22	1.78	0.63	
fun		0.37	3.79	-inf	
heaven		0.41	2.80	6.60	
……					

PMI tricks

- Zero all negative values (PPMI)
  - Avoid –inf and unreliable negative values
- Counter bias towards rare events
  - Smooth probabilities

Similarity

- Regardless of vector representation, classic use of vector is comparison with other vector
  - Though vectors can also be used directly as features
- For IR: find documents most similar to query



Cosine similarity

The cosine of the angle between two vectors is the dot product of the two vectors divided by the product of their norms:

$$\cos\theta = \frac{\vec{a}\cdot\vec{b}}{|\vec{a}||\vec{b}|}$$

Where

$$\vec{a}\cdot\vec{b} = \sum_{i=1}^{N} a_i b_i$$

And

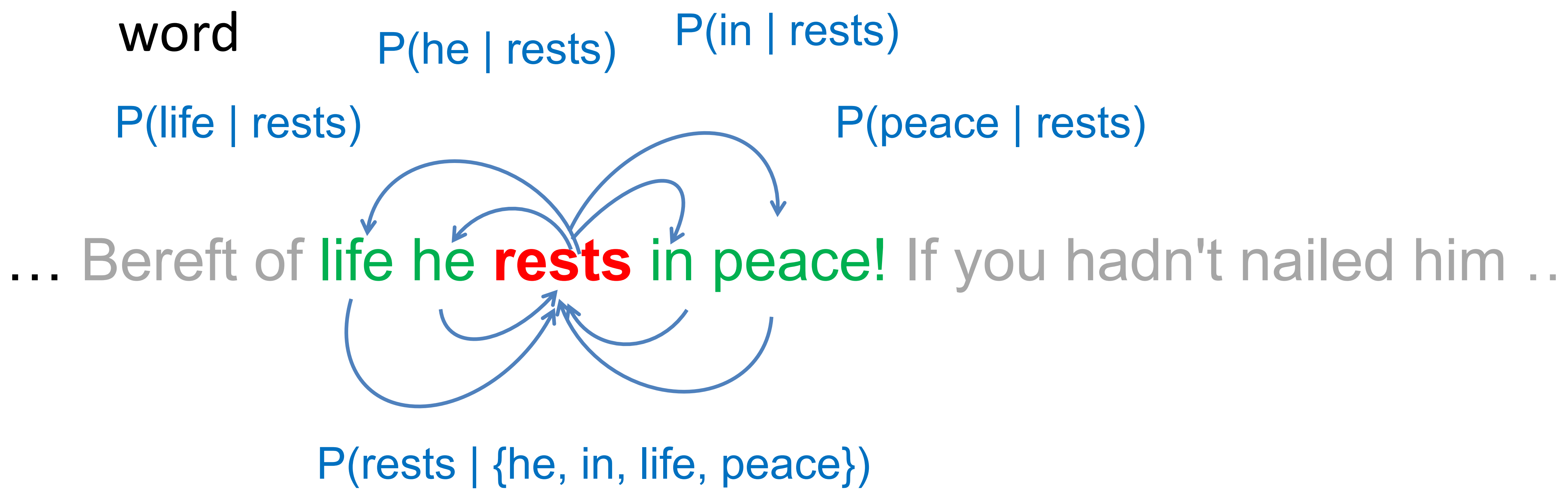
$$|\vec{a}| = \sqrt{\sum_{i=1}^{N} {a_i}^2}$$

Skip-gram: Factored Prediction

- Neural network inspired approaches seek to learn vector representations of words and their contexts
- Key idea
  - *Word embeddings should be similar to embeddings of neighbouring words*
  - *And dissimilar to other words that don't occur nearby*
- Using vector dot product for vector 'comparison'
  - $u \,.\, v = \sum_j u_j \, v_j$
- As part of a '*classifier*' over a word and its immediate context

Skip-gram: Factored Prediction

- Framed as learning a classifier…
  - **Skip-gram**: predict words in local context surrounding given word



  - **CBOW**: predict word in centre, given words in the local surrounding context
- Local context means words within L positions, e.g., L=2

Skip-gram model

- Generates each word in context given centre word

P(he | rests) P(in | rests)

P(life | rests) P(peace | rests)

… Bereft of life he **rests** in peace! If you hadn't nailed him …

- Total probability defined as
  - Where subscript denotes position in running text

$$\prod_{l \in -L,\ldots,-1,1,\ldots,L} P(w_{t+l}|w_t)$$

- Using a ~logistic regression model

$$P(w_k|w_j) = \frac{\exp(c_{w_k} \cdot v_{w_j})}{\sum_{w' \in V} \exp(c_{w'} \cdot v_{w_j})}$$

Embedding parameterisation

- Two parameter matrices, with d-dimensional embedding for all words

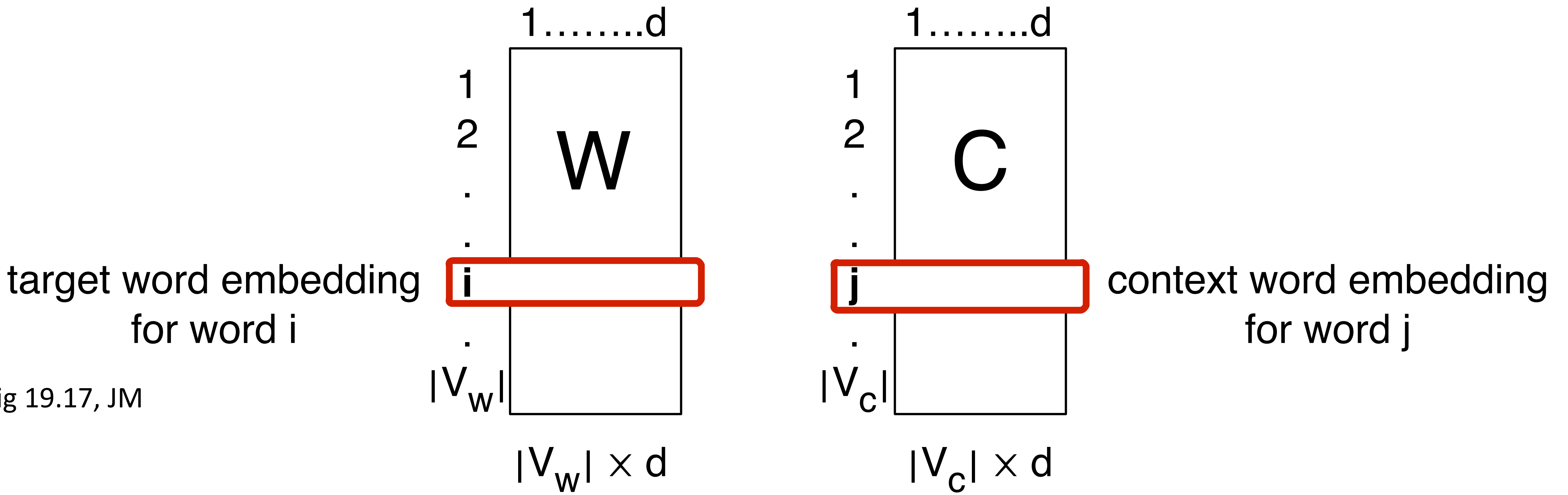


Fig 19.17, JM

- Words are numbered, e.g., by sorting vocabulary and using word location as its index

One-hot vectors and embeddings

- Word types are assigned numbers,
  e.g., “cat” = 17235th word
  * The embeddings for “cat” are then:
    - V_{17235} = [1.23, 0.8, -0.15, 0.7, 1.1, -1.3, ...] (d-dim. vector)
    - C_{17235} = [0.32, 0.1, 0.27, 2.5, -0.1, 0.45, ...] (d-dim. vector)
  * Using a separate embedding for “cat” appearing in the centre and appearing in the context of another word
- A “one-hot vector” is all 0s, with a single 1 at index i
  * E.g., x = “cat” = [0,0,0, ..., 0,1,0, ..., 0]
    where index 17235 is set to 1, all other V-1 entries are 0
  * This allows us to write $V_{\text{"cat"}}$ as V x

Skip-gram model

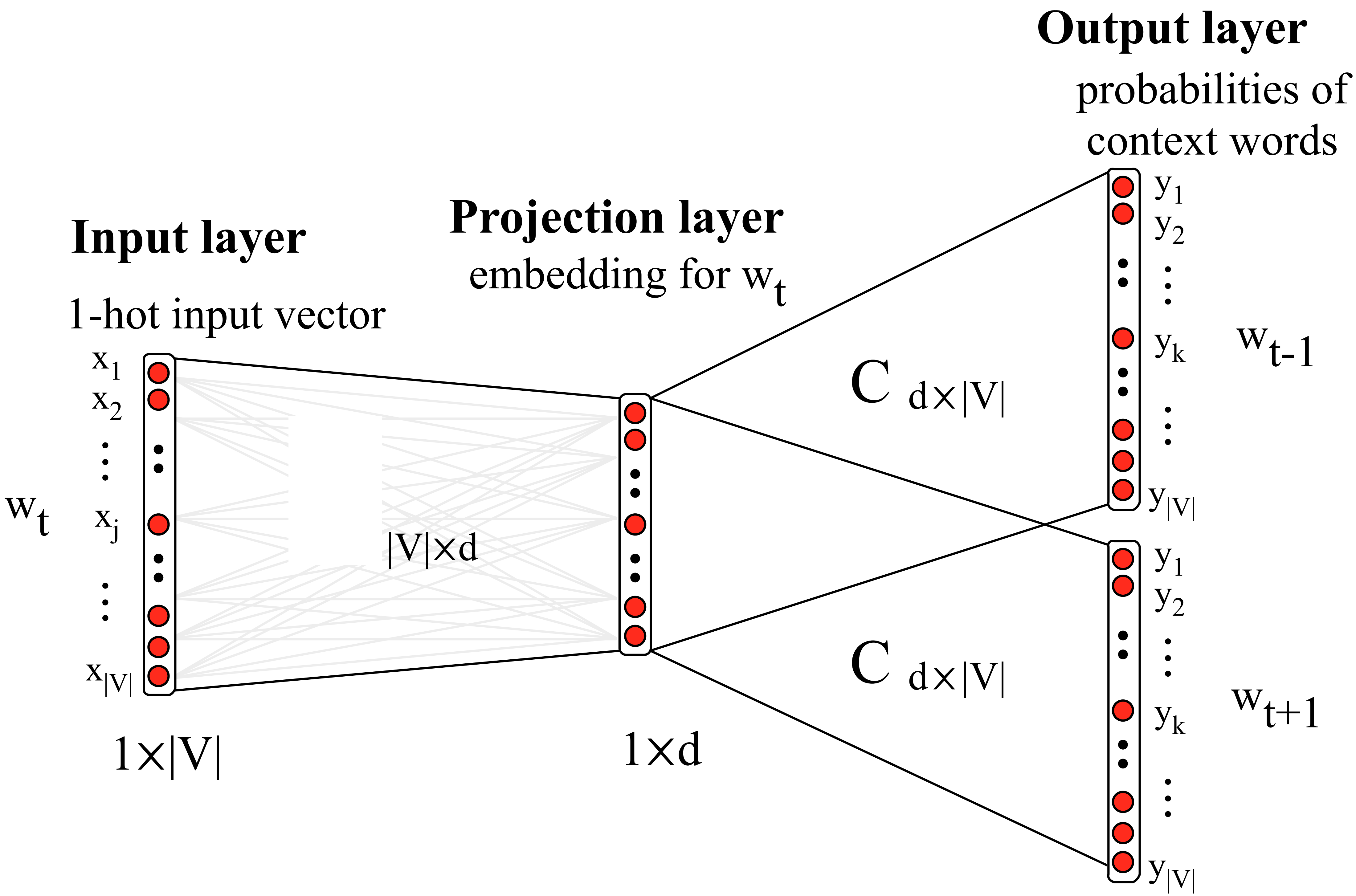


Fig 19.18, JM

Training the skip-gram model

- Train to *maximise likelihood* of **raw text**
- Reduce problem to binary classification, distinguish real context words from random "negative samples"

$$P(+|w_k, w_j) = \frac{1}{1 + \exp(-c_k \cdot v_j)}$$

$$P(-|w_k, w_j) = 1 - \frac{1}{1 + \exp(-c_k \cdot v_j)}$$

```
... lemon,  a [tablespoon of apricot jam,     a] pinch ...
                 c1         c2     t     c3       c4
```

positive examples +

t	c
apricot	tablespoon
apricot	of
apricot	preserves
apricot	or

negative examples -

t	c	t	c
apricot	aardvark	apricot	twelve
apricot	puddle	apricot	hello
apricot	where	apricot	dear
apricot	coaxial	apricot	forever

Source: JM3 Ch 6

Evaluating word vectors

- Lexicon style tasks
  - *WordSim-353* are pairs of nouns with judged relatedness
  - *SimLex-999* also covers verbs and adjectives
  - *TOEFL* asks for closest synonym as multiple choice
  - …
- Word analogy task
  - Man is to King as Woman is to ???
  - France is to Paris as Italy is to ???
  - Evaluate where in the ranked predictions the correct answer is, given tables of known relations

Evaluating word vectors

- Best evaluation is in other downstream tasks
  - Use bag-of-word embeddings as a feature representation in a classifier (e.g., sentiment, QA, tagging etc.)
  - First layer of most deep learning models is to embed input text; use pre-trained word vectors as embeddings, possibly with further training ("fine-tuning") for specific task
- Recently "contextual word vectors" shown to work even better, ELMO (AI^2), BERT (Google AI), …

Pointers to software

- Word2Vec
  - C implementation of Skip-gram and CBOW
    https://code.google.com/archive/p/word2vec/
- GenSim
  - Python library with many methods include LSI, topic models and Skipgram/CBOW
    https://radimrehurek.com/gensim/index.html
- GLOVE
  - http://nlp.stanford.edu/projects/glove/

Further reading

- Either one of:
  - E18, 14-14.6 (skipping 14.4)
  - JM3, Ch 6