

Javid Huseynov, Ph.D. Thursday, February 27, 2020



Week 6 Agenda

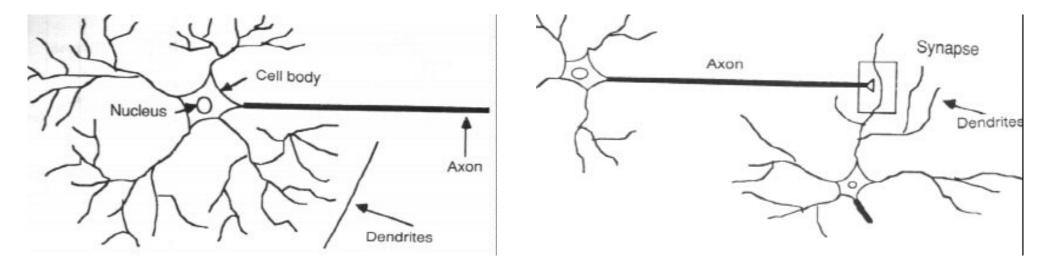


- Neural Networks Overview
- Vector-Space Model
- Sentence Vectors
- Word Vectors: Concept
- Co-occurrence Matrix
- Singular Value Decomposition (SVD)
- Word2Vec
- Class Exercises

Neural network: Bio inspiration



• Almost all living species can learn and react to changes in their environment using their nervous system

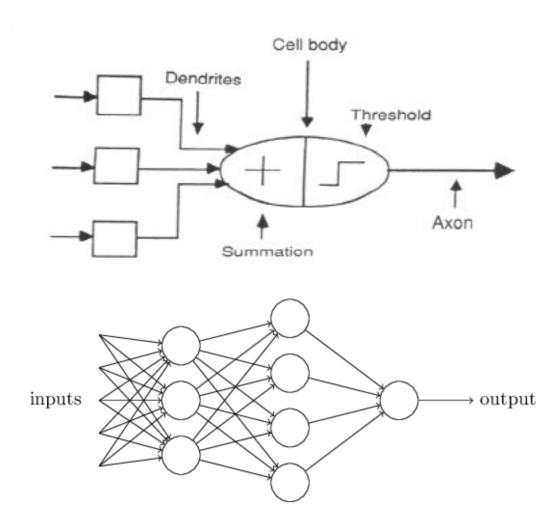


• An artificial mathematical model can reproduce the behavior of the central nervous system

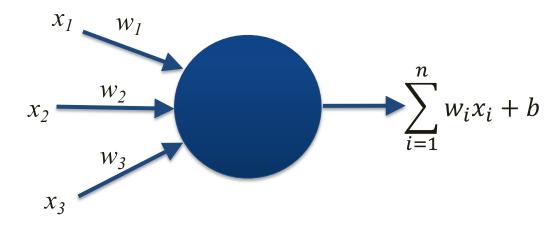
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From human to artificial neurons





- Simple Neuron Perceptron Model
- (Rosenblatt 1958)



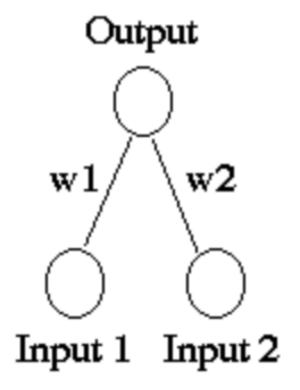
output =
$$\begin{cases} 0 & \text{if } \sum_{j} w_{j} x_{j} \leq \text{ threshold} \\ 1 & \text{if } \sum_{j} w_{j} x_{j} > \text{ threshold} \end{cases}$$

2-layer Perceptron Limitation: Exclusive-OR (XOR) problem



Minsky & Pappert 1969

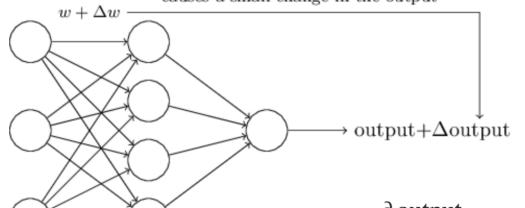
Input 1	Input 2	Output
1	1	0
1	0	1
0	1	1
0	0	0



From Perceptron to Activation Function

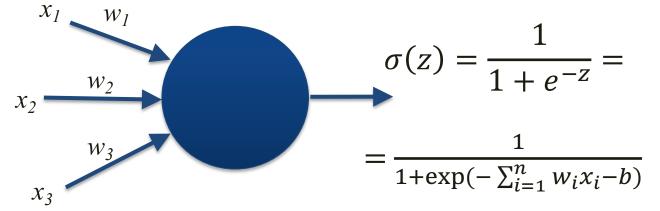


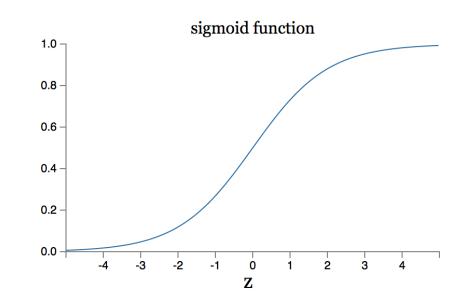
small change in any weight (or bias) causes a small change in the output



- Set of small changes in connection weights can alter the output significantly
- To smooth this impact, sigmoid activation function is used

$$\Delta \text{output} \approx \sum_{j} \frac{\partial \text{ output}}{\partial w_{j}} \Delta w_{j} + \frac{\partial \text{ output}}{\partial b} \Delta b,$$





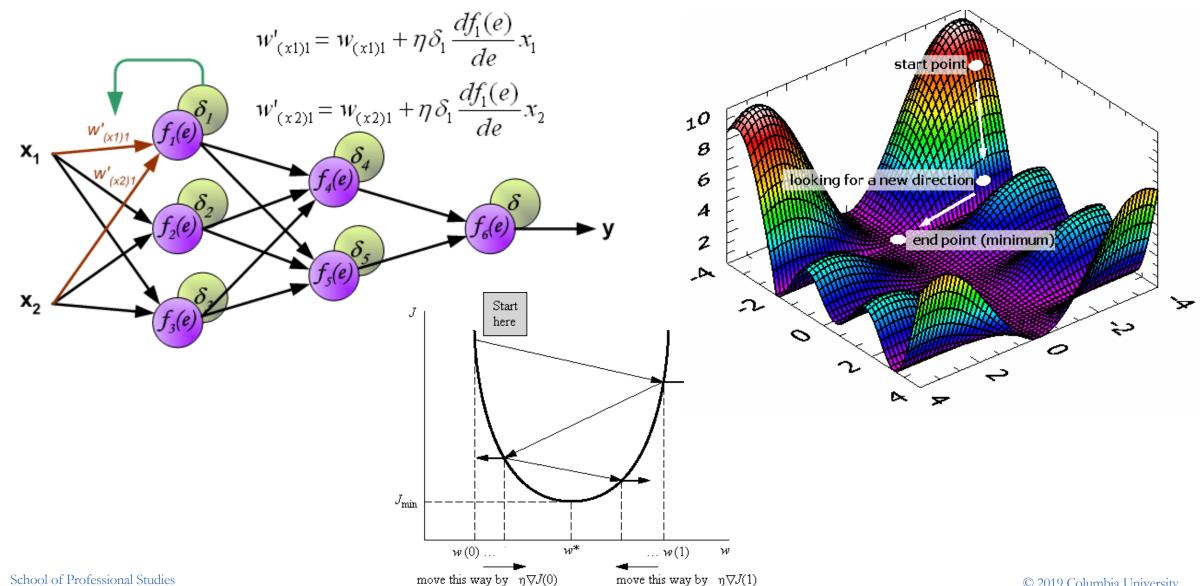
Types of Activation Functions



Name Sort ascending	Plot ≑	Equation ÷	Derivative (with respect to x)	Range +
Identity		f(x)=x	f'(x)=1	$(-\infty,\infty)$
Binary step		$f(x) = egin{cases} 0 & ext{for } x < 0 \ 1 & ext{for } x \geq 0 \end{cases}$	$f'(x) = \left\{egin{array}{ll} 0 & ext{for } x eq 0 \ ? & ext{for } x = 0 \end{array} ight.$	$\{0,1\}$
Logistic (a.k.a. Soft step)		$f(x)=rac{1}{1+e^{-x}}$	$f^{\prime}(x)=f(x)(1-f(x))$	(0,1)
TanH		$f(x)= anh(x)=rac{2}{1+e^{-2x}}-1$	$f^{\prime}(x)=1-f(x)^{2}$	(-1,1)
ArcTan		$f(x)= an^{-1}(x)$	$f'(x)=rac{1}{x^2+1}$	$\left(-rac{\pi}{2},rac{\pi}{2} ight)$
Softsign [7][8]		$f(x) = \frac{x}{1+ x }$	$f'(x) = rac{1}{(1+ x)^2}$	(-1,1)
Rectified linear unit (ReLU) ^[9]		$f(x) = egin{cases} 0 & ext{for } x < 0 \ x & ext{for } x \geq 0 \end{cases}$	$f'(x) = egin{cases} 0 & ext{for } x < 0 \ 1 & ext{for } x \geq 0 \end{cases}$	$[0,\infty)$

Backpropagation & conjugate gradient





Backpropagation Step-by-Step



- Visit the following site to see a simple but great overview of the operation of the backpropagation algorithm with numbers:
- https://mattmazur.com/2015/03/17/a-step-by-step-backpropagation-example/

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Neural Network Applications



Neural networks in pop culture

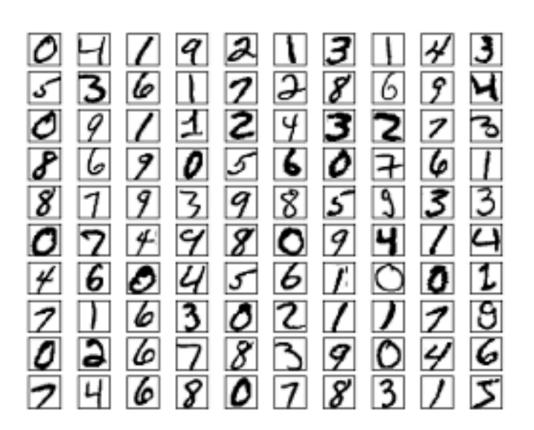


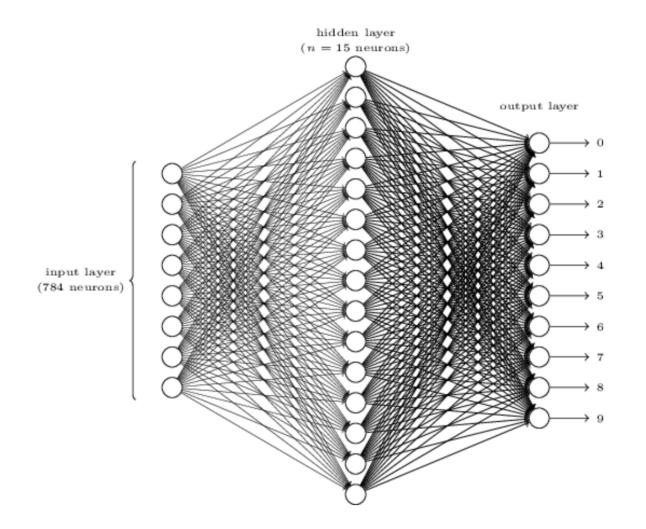
- Natural Language Processing
- Signal Processing | Time Series
- Stock Market Forecasting
- Credit Risk Assessment
- Image Processing | Character Recognition
- Speech Recognition
- Self-driving cars
- Sports Prediction
- Any other field where extra brain can be useful ©

Use Case: Scanned Digit Recognition with Neural Networks



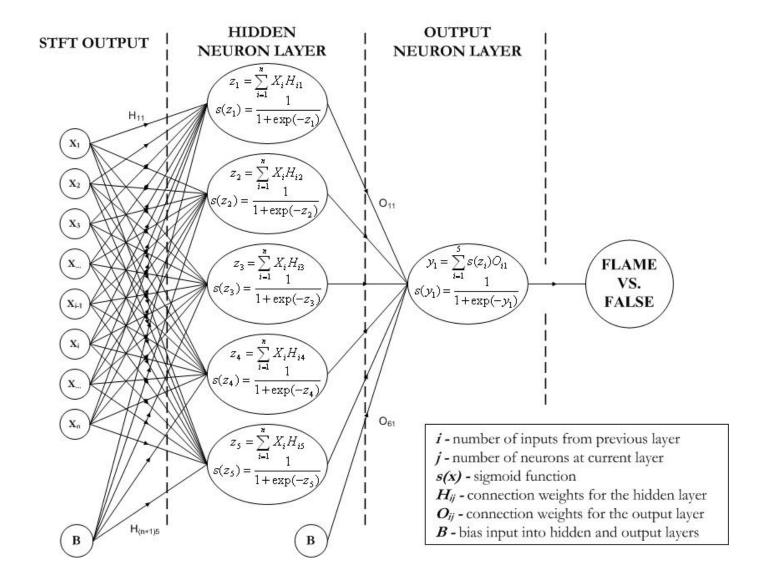
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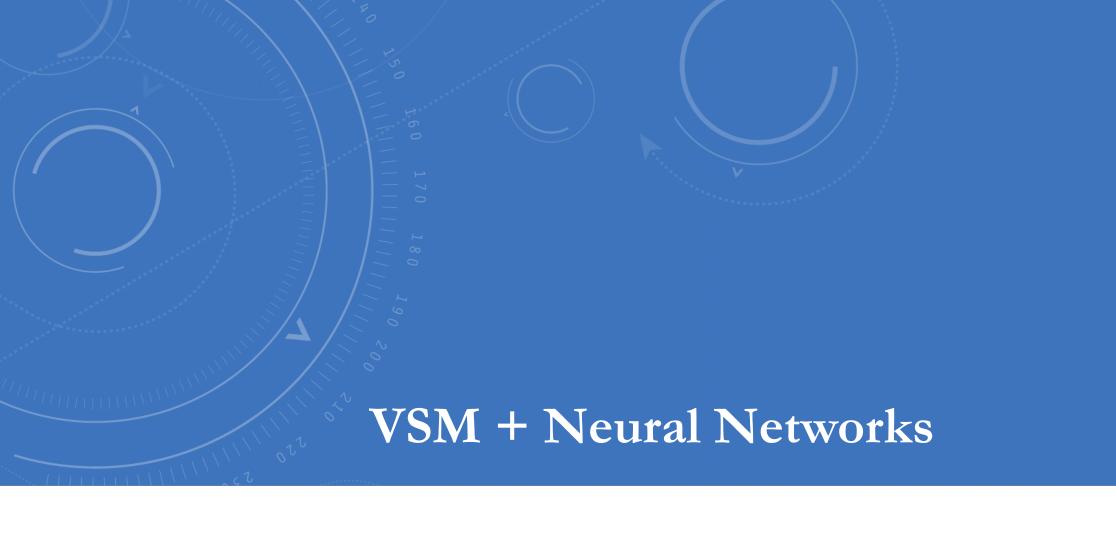




Another Use Case: Flame Detection using Neural Networks







IR Vector-Space Model



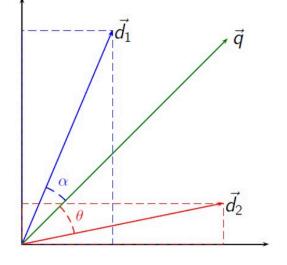
 An algebraic representation of text documents or queries as vectors

$$d_j = (w_{1,j}, w_{2,j}, \dots, w_{t,j}) \ q = (w_{1,q}, w_{2,q}, \dots, w_{n,q})$$

Cosine similarity

$$\|\mathbf{q}\| = \sqrt{\sum_{i=1}^n q_i^2}$$

$$\cos heta = rac{\mathbf{d_2} \cdot \mathbf{q}}{\|\mathbf{d_2}\| \|\mathbf{q}\|}$$



$$ext{sim}(d_j,q) = rac{\mathbf{d_j} \cdot \mathbf{q}}{\|\mathbf{d_j}\| \, \|\mathbf{q}\|} = rac{\sum_{i=1}^N w_{i,j} w_{i,q}}{\sqrt{\sum_{i=1}^N w_{i,j}^2} \sqrt{\sum_{i=1}^N w_{i,q}^2}}$$

One-Hot Encoding (Word Embedding)

- Given "Can I eat the pizza" of N=5
 - 1. Convert to lower case
 - 2. Sort the words in alphabetical order
 - 3. Give numerical labels to each word: can:0, i:2, eat:1, the:4, pizza:3
 - 4. Transform to binary vectors

```
[[1. 0. 0. 0. 0.] #can
[0. 0. 1. 0. 0.] #i
[0. 1. 0. 0. 0.] #eat
[0. 0. 0. 0. 1.] #the
[0. 0. 0. 1. 0.]] #pizza
```

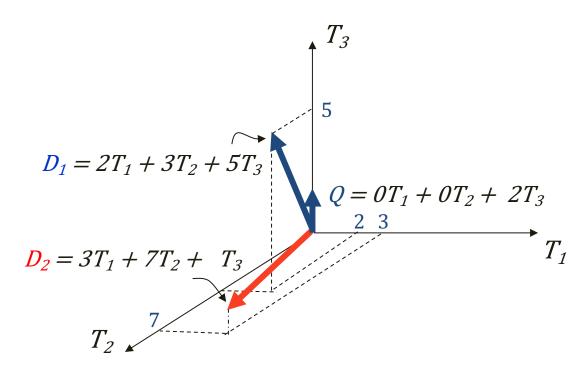
Sentence Vectors



- Collection of *n* documents with **m** terms can be represented in the vector space model by a term-document matrix.
- An entry in the matrix corresponds to the "weight" of a term in the document;
 - zero means the term has no significance or it simply doesn't exist in the document

$$\begin{pmatrix} & T_1 & T_2 & \dots & T_m \\ D_1 & w_{11} & w_{21} & \dots & w_{m1} \\ D_2 & w_{12} & w_{22} & \dots & w_{m2} \\ \vdots & \vdots & \vdots & & \vdots \\ D_n & w_{1n} & w_{2n} & \dots & w_{mn} \end{pmatrix}$$

• tf-idf weighting: $w_{ij} = tf_{ij}*idf_i = tf_{ij} \log_2 (N/df_i)$

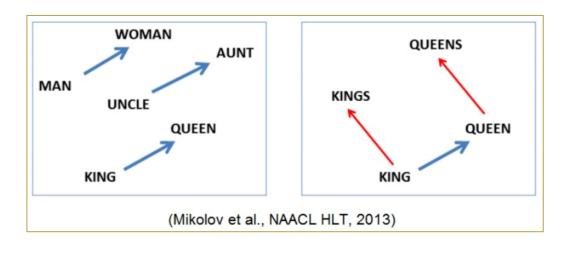


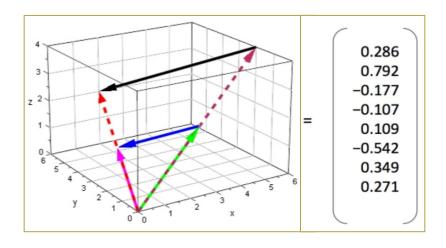
- Is D_1 or D_2 more similar to Q?
- How to measure the degree of similarity? Distance? Angle? Projection?

"You shall know a word by the company it keeps" ~ J.R. Firth 1957



- Vectors are directions in space, which can also encode relationships:
 - e.g. man is to woman as king is to queen





- One of the most successful ideas in modern statistical NLP
 - ...government debt problem turning into banking crises as has happened in...
 - ...saying that Europe needs unified banking regulation to replace the hodgepodge...

surrounding words capture the context of the word banking

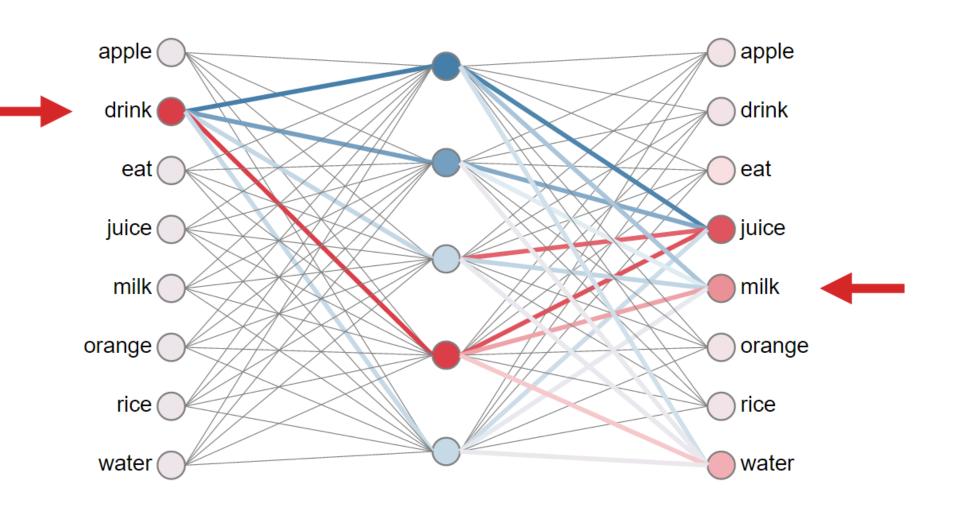
Word vectors: Learning with Neural Networks



Neural Networkbased Word Embedding Models







Co-occurrence Matrix



```
Corpus = {"I like deep learning"
           "I like NLP"
           "I enjoy flying"}
```

Context = previous word and next word

counts	1	like	enjoy	deep	learning	NLP	flying	
1	0	2	1	0	0	0	0	0
like	2	0	0	1	0	1	0	0
enjoy	1	0	0	0	0	0	1	0
deep	0	1	0	0	1	0	0	0
learning	0	0	0	1	0	0	0	1
NLP	0	1	0	0	0	0	0	1
flying	0	0	1	0	0	0	0	1
	0	0	0	0	1	1	1	0

Singular Value Decomposition (SVD)



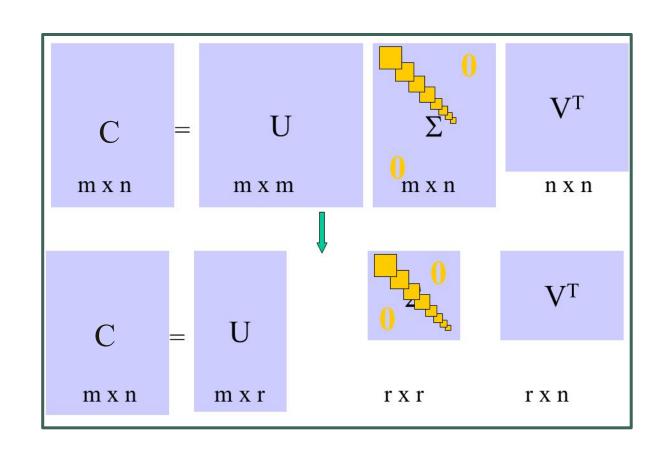
• Any real *m x n* matrix *C* can be decomposed into:

$$C = U\Sigma V^{T}$$

- U is $m \times n$, column orthonormal $(U^TU = I)$
- Σ is $n \times n$ and diagonal:

•
$$\Sigma = diag(\sigma_1, \sigma_2, ..., \sigma_n)$$

- σ_1 are called *singular* values of C
- $\sigma_1 \ge \sigma_2 \ge \dots \ge \sigma_n \ge 0$
- V is $\mathbf{n} \times \mathbf{n}$ and orthonormal $(VV^T = V^TV = I)$



SVD Example (LSA)



Term-Document Matrix $C = U\Sigma V^T$

U	1	2	3	4	5
ship	-0.44	-0.30	0.57	0.58	0.25
boat	-0.13	-0.33	-0.59	0.00	0.73
ocean	-0.48	-0.51	-0.37	0.00	-0.61
wood	-0.70	0.35	0.15	-0.58	0.16
tree	-0.26	0.65	-0.41	0.58	-0.09

Σ	1	2	3	4	5
1	2.16	0.00	0.00	0.00	0.00
2	0.00	1.59	0.00	0.00	0.00
3	0.00	0.00	1.28	0.00	0.00
4	0.00	0.00	0.00	1.00	0.00
5	0.00	0.00 0.00 0.00	0.00	0.00	0.39

С	d_1	d_2	d_3	d_4	d_5	<i>d</i> ₆
ship	1	0	1	0	0	0
boat	0	1	0	0	0	0
ocean	1	1	0	0	0	0
wood	1	0	0	1	1	0
tree	0	0	0	1	0	1

V^T	d_1	d_2	d_3	d ₄	d_5	d_6
1	-0.75	-0.28			-0.33	-0.12
2	-0.29	-0.53	-0.19	0.63	0.22	0.41
3	0.28	-0.75	0.45	-0.20	0.12	-0.33
4	0.00	0.00	0.58	0.00	-0.58	0.58
5	-0.53	0.29	0.63	0.19	0.41	-0.22

SVD Example (LSA)



Dimensionality reduction $C_2 = U\Sigma_2 V^T$

U	1	2	3	4	5
ship	-0.44	-0.30	0.00	0.00	0.00
boat	-0.13	-0.33	0.00	0.00	0.00
ocean	-0.48	-0.51	0.00	0.00	0.00
wood	-0.70	0.35	0.00	0.00	0.00
tree	-0.26	0.65	0.00	0.00	0.00

Σ_2	1	2	3	4	5
1	2.16	0.00	0.00	0.00	0.00
2	0.00	1.59	0.00	0.00	0.00
3	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00

C_2	d_1	d_2	d_3	d_4	d_5	d_6
ship	0.85	0.52	0.28	0.13	0.21	-0.08
boat	0.36	0.36	0.16	-0.20	-0.02	-0.18
ocean	1.01	0.72	0.36	-0.04	0.16	-0.21
wood	0.97	0.12	0.20	1.03	0.62	0.41
tree	0.12	-0.39	-0.08	0.90	0.41	0.49

V^T	d_1	d_2	d ₃	d_4	d_5	d_6
1	-0.75	-0.28	-0.20	-0.45	-0.33	-0.12
2	-0.29	-0.53	-0.19	0.63	0.22	0.41
3	0.00	0.00	0.00	0.00	0.00	0.00
4	0.00	0.00	0.00	0.00	0.00	0.00
5	0.00	0.00	0.00	0.00	0.00	0.00

SVD Example (LSA)



- Similarity of d₂ and d₃ in the original space: 0.
- Similarity of d_2 and d_3 in the reduced space: $0.52 * 0.28 + 0.36 * 0.16 + 0.72 * 0.36 + 0.12 * 0.20 + -0.39 * -0.08 <math>\approx$ **0.52**

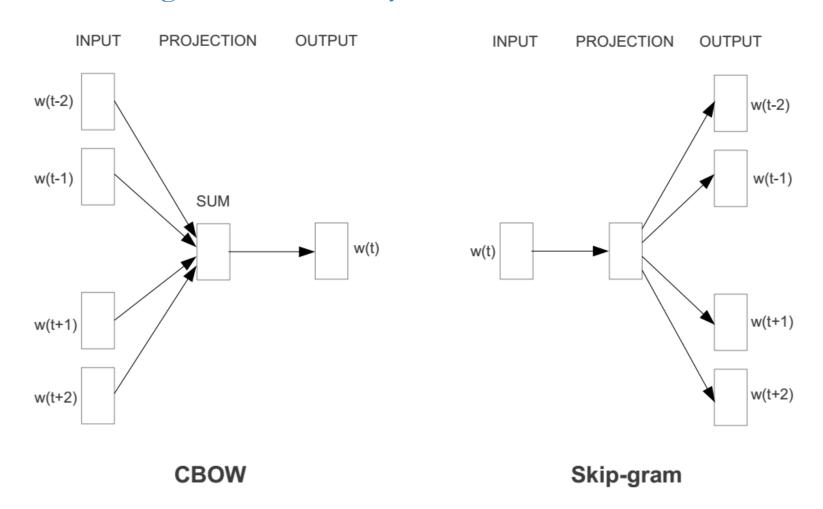
C	d_1	d_2	d_3	d_4	d_5	d_6
ship	1	0	1	0	0	0
boat	0	1	0	0	0	0
ocean	1	1	0	0	0	0
wood	1	0	0	1	1	0
tree	0	0	0	1	0	1

C_2	d_1	d_2	d_3	d_4	d_5	d_6
ship	0.85	0.52	0.28	0.13	0.21	-0.08
boat	0.36	0.36	0.16	-0.20	-0.02	-0.18
ocean	1.01	0.72	0.36	-0.04	0.16	-0.21
wood	0.97	0.12	0.20	1.03	0.62	0.41
tree	0.12	0.52 0.36 0.72 0.12 -0.39	-0.08	0.90	0.41	0.49

Word2vec



• Represent the meaning of the word by its context



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Word2Vec Learning models



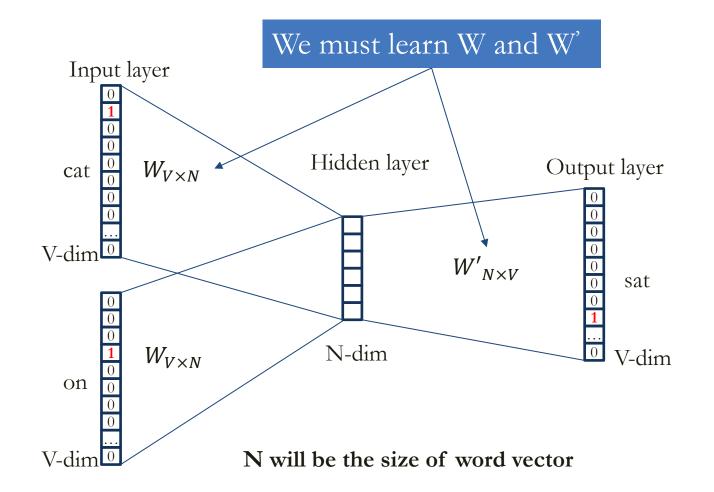
- Continuous Bag of Words (CBOW):
- Given the context predict the word:
 - $\bullet W_{i-2}, W_{i-1}, W_{i}, W_{i+1}, W_{i+2}$
- Example: The cat ate ____.
 - Fill in the blank, e.g. "food".
- Faster to train
- Works well for large amount of training data

- Continuous Skip-Gram:
- Given the word predict the context:
 - W_{i-2} , W_{i-1} , W_{i} , W_{i+1} , W_{i+2}
- Ex: ____ food.
 - Fill in the blank, e.g. "The cat ate"
- Slower to train
- Works better for infrequent words

Word2Vec: CBOW Example



"the cat ____ on floor" **INPUT PROJECTION** OUTPUT the w(t-2) cat w(t-1) SUM sat w(t) on w(t+1) floor w(t+2)



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Learning Connection Weights



