

# Data Mining and Machine Learning

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## Latent Semantic Analysis (LSA)

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# Objectives

- To understand, intuitively, how Latent Semantic Analysis (LSA) can discover latent topics in a corpus

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# Vector Notation

- The vector representation  $\text{vec}(d)$  of  $d$  is the  $V$  dimensional vector:

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$$(0, \dots, 0, w_{i(1),d}, 0, \dots, 0, w_{i(2),d}, 0, \dots, 0, w_{i(M),d}, 0, \dots, 0)$$

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$i(1)^{\text{th}}$   
place

$i(2)^{\text{th}}$   
place

$i(M)^{\text{th}}$   
place

Notice that this is the weighting – i.e. the term frequency times the inverse document frequency

$$w_{i(1),d} = f_{i(1),d} \times \text{IDF}(i(1)) \text{ from text IR}$$

# Latent Semantic Analysis (LSA)

- Suppose we have a real corpus with a large number of documents
- For each document  $d$  the dimension of the vector  $vec(d)$  will typically be several (tens of) thousands
- Let's focus on just 2 of these dimensions, corresponding, say, to the words 'sea' and 'beach'
- Intuitively, often, when a document  $d$  includes 'sea' it will also include 'beach'

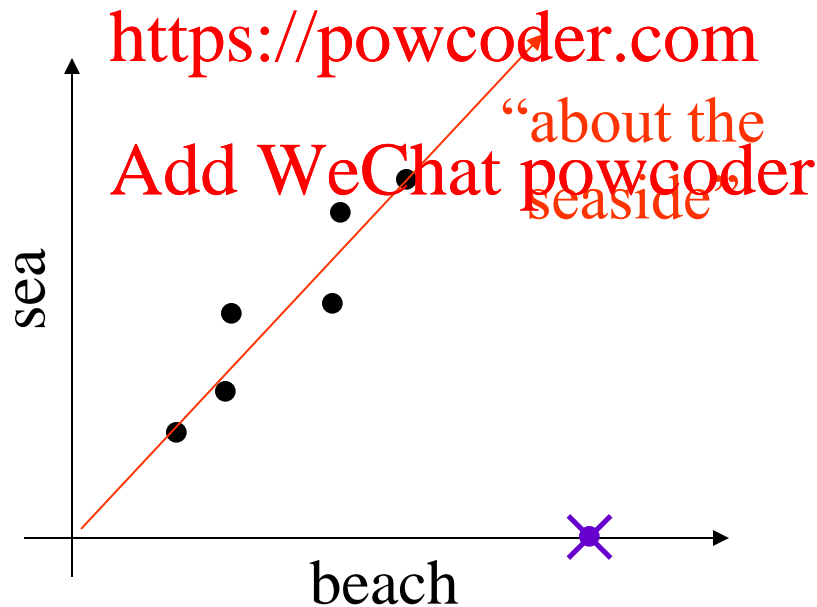
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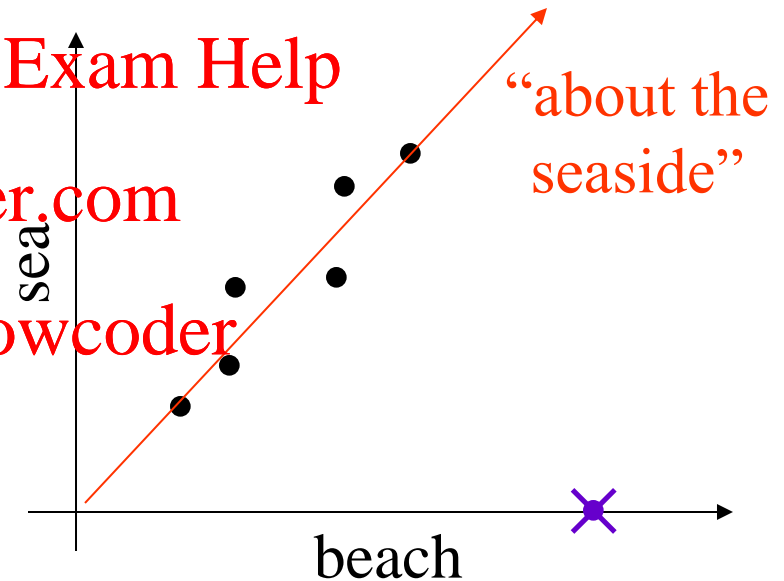
# LSA continued

- Equivalently, if  $vec(d)$  has a non-zero entry in the ‘sea’ component, it will often have a non-zero entry in the ‘beach’ component



# Latent Semantic Classes

- If we can detect this type of structure, then we can discover relationships between words automatically, from data
- In the example we have found an equivalence set of terms, including ‘beach’ and ‘sea’, which is ‘about the seaside’



# Finding Latent Semantic Classes

- LSA involves some advanced linear algebra – the description here is just an outline
- First construct the ‘word-document’ matrix  $A$
- Then decompose  $A$  using Singular Value Decomposition (SVD)
  - SVD is a standard technique from matrix algebra
  - Packages such as MATLAB have SVD functions:  
`>>[U,S,V]=svd(A)`

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# Singular Value Decomposition

- Remember eigenvector decomposition?
- An eigenvector of a square matrix  $A$  is a vector  $e$  such that  $Ae = \lambda e$ , where  $\lambda$  is a scalar
- For certain matrices  $A$  we can write  $A = UDU^T$ , where  $U$  is an **orthogonal matrix** (rotation) and  $D$  is **diagonal**
  - The elements of  $D$  are the eigenvalues
  - The columns of  $U$  are the eigenvectors
- You can think of SVD as a more general version of eigenvector decomposition, which works for general matrices



# Word-Document Matrix

- The Word-Document matrix is a  $N \times V$  matrix whose  $n^{th}$  row is  $vec(d_n)$

term

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$$A = \begin{bmatrix} w_{t_1 d_1} & w_{t_2 d_1} & \cdots & w_{t_m d_1} & \cdots & w_{t_V d_1} \\ w_{t_1 d_2} & w_{t_2 d_2} & \cdots & w_{t_m d_2} & \cdots & w_{t_V d_2} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{t_1 d_n} & w_{t_2 d_n} & \cdots & w_{t_m d_n} & \cdots & w_{t_V d_n} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ w_{t_1 d_N} & w_{t_2 d_N} & \cdots & w_{t_m d_N} & \cdots & w_{t_V d_N} \end{bmatrix}$$

document

Weighting for term  $t_m$  in  $d_n$

# Singular Value Decomposition (SVD)

$N$ =number of docs,  $V$ =vocabulary size

$$A = USV^T$$

Direction of most significant correlation

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$$A = \begin{bmatrix} u_{11} & u_{12} & \dots & u_{1N} \\ u_{21} & u_{22} & \dots & u_{2N} \\ \vdots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ u_{N1} & u_{N2} & \dots & u_{NN} \end{bmatrix} \begin{bmatrix} s_1 & 0 & \dots & 0 & \dots & 0 \\ 0 & s_2 & \dots & 0 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & s_N & \dots & 0 \end{bmatrix} \begin{bmatrix} v_{11} & v_{21} & \dots & v_{i1} & \dots & v_{V1} \\ v_{12} & v_{22} & \dots & v_{i2} & \dots & v_{V2} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ v_{1V} & v_{2V} & \dots & v_{iV} & \dots & v_{VV} \end{bmatrix}$$

$N$  (rows of  $A$ )

$V$  (columns of  $A$ )

$V$  (columns of  $V^T$ )

‘Strength’ of most significant correlation

# Interpretation of LSA

- The matrices  $U$  and  $V$  are orthogonal matrices
  - Their entries are real numbers
  - $U$  is  $N \times N$  ( $N$  is the number of documents) and  $V$  is  $V \times V$  ( $V$  is the vocabulary size)
  - They satisfy  $UU^T = I = U^T U$ ,  $VV^T = I = V^T V$
- The singular values  $s_1, \dots, s_N$  are positive and satisfy  $s_1 \geq s_2 \geq \dots \geq s_N$
- The off-diagonal entries of  $S$  are all zero

# Interpretation of LSA (continued)

- Focussing on  $V$ :
  - The columns of  $V$ ,  $\{v_1, \dots, v_V\}$  are unit vectors and orthogonal to each other
  - They form a new orthonormal basis (coordinate system) for the document vector space
  - Each column of  $V$  is a document vector corresponding to a semantic class (topic) in the corpus
  - The importance of the topic corresponding to  $v_n$  is indicated by the size of the singular value  $s_n$

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# Interpretation of LSA (continued)

- Since  $v_n$  is a document vector, its  $j^{\text{th}}$  value corresponds to TF-IDF weight for  $j^{\text{th}}$  term in the vocabulary for the corresponding document/topic
- This can be used to interpret the topic corresponding to  $v_n$  – a large value of  $v_{nj}$  indicates that the  $j^{\text{th}}$  term in the vocabulary is significant for the topic

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# Interpretation of LSA (continued)

- Now consider  $U$
- It is easy to show that

$$Av_n = USV^T v_n = s_n u_n$$

- While  $v_n$  describes the  $n^{\text{th}}$  topic as a combination of terms/words,  $u_n$  describes it as a combination of documents

# Topic-based representation

- Columns of  $V$ ,  $v_1, \dots, v_V$  are an **orthonormal basis** (coordinate system) for the document vector space
- If  $d$  is a document,  $vec(d) \cdot v_n$  is the magnitude of the component of  $vec(d)$  in the direction of  $v_n$
- ..the component of  $vec(d)$  corresponding to topic  $n$

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- Hence the vector  $top(d) = \begin{bmatrix} vec(d) \cdot v_1 \\ vec(d) \cdot v_2 \\ \vdots \\ vec(d) \cdot v_V \end{bmatrix} = V^T vec(d)$

is a **topic-based representation** of  $d$  in terms of  $v_1, \dots, v_V$

# More information about LSA

- See:

Landauer, T.K. and Dumais, S.T., “A solution to Platos problem: The Latent Semantic Analysis theory of the acquisition, induction and representation of knowledge”, *Psychological Review* 104(2), 211-240 (1997)

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# Thoughts on document vectors

- Once  $d$  is replaced by  $vec(d)$  it becomes a point in a vector space
- How does the structure of the vector space reflect the properties of the documents in it?
- Do clusters of vectors correspond to semantically related documents?
- Can we partition the vector space into semantically different regions?
- These ideas are a link between IR and Data Mining

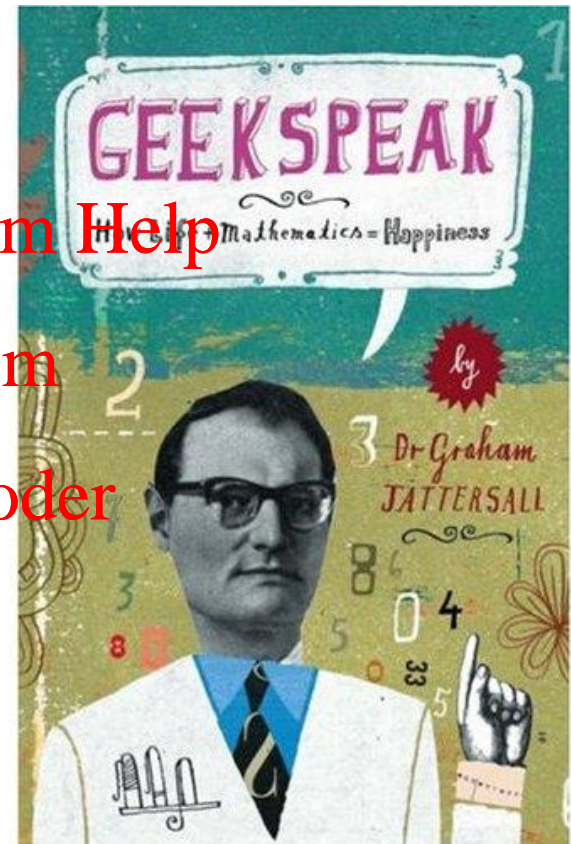
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# For an alternative perspective...

- Chapter 14: “The cunning fox”
- Application of LSA to ‘dating agency’ personal adverts
- LSA suggests that the meaning of a personal advert can be expressed as a weighted combination of a few basic ‘concepts’



*Dr Graham Tattersall, “Geekspeak: How life + mathematics = happiness”, 2007*

# Summary

- Latent Semantic Analysis

- Interpretation of LSA

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