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15-826: Multimedia Databases and Data Mining

Lecture #19: SVD - part II (case studies)

C. Faloutsos

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Must-read Material

- MM Textbook Appendix D

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Outline

Goal: 'Find similar / interesting things'

- Intro to DB
- Indexing - similarity search
- Data Mining

Indexing - Detailed outline

- primary key indexing
- secondary key / multi-key indexing
- spatial access methods
- fractals
- text
- Singular Value Decomposition (SVD)
- multimedia
- ...

SVD - Detailed outline

- Motivation
- Definition - properties
- Interpretation
- Complexity
- Case studies
- SVD properties
- Conclusions

SVD - Case studies

- multi-lingual IR; LSI queries
- compression
- PCA - 'ratio rules'
- Karhunen-Lowe transform
- query feedbacks
- google/Kleinberg algorithms

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Case study - LSI

Q1: How to do queries with LSI?

Q2: multi-lingual IR (english query, on spanish text?)

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Case study - LSI

Q1: How to do queries with LSI?

Problem: Eg., find documents with 'data'

$$\begin{array}{c} \\ \\ \text{CS} \\ \\ \\ \text{MD} \\ \\ \end{array} \begin{array}{c} \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \end{array} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \text{x} \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \text{x} \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

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Case study - LSI

Q1: How to do queries with LSI?

A: map query vectors into 'concept space' – how?

$$\begin{array}{c} \\ \\ \text{CS} \\ \\ \\ \text{MD} \\ \\ \end{array} \begin{array}{c} \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\ \begin{bmatrix} 1 & 1 & 1 & 0 & 0 \\ 2 & 2 & 2 & 0 & 0 \\ 1 & 1 & 1 & 0 & 0 \\ 5 & 5 & 5 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 0 & 0 & 0 & 3 & 3 \\ 0 & 0 & 0 & 1 & 1 \end{bmatrix} \end{array} = \begin{bmatrix} 0.18 & 0 \\ 0.36 & 0 \\ 0.18 & 0 \\ 0.90 & 0 \\ 0 & 0.53 \\ 0 & 0.80 \\ 0 & 0.27 \end{bmatrix} \text{x} \begin{bmatrix} 9.64 & 0 \\ 0 & 5.29 \end{bmatrix} \text{x} \begin{bmatrix} 0.58 & 0.58 & 0.58 & 0 & 0 \\ 0 & 0 & 0 & 0.71 & 0.71 \end{bmatrix}$$

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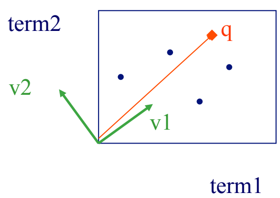
Case study - LSI

Q1: How to do queries with LSI?

A: map query vectors into 'concept space' – how?

$$q = \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \\ \end{array}$$
$$\begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix}$$



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Case study - LSI

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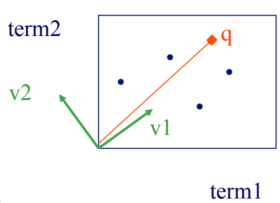

A: inner product (cosine similarity) with each 'concept' vector v_i

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Case study - LSI

Q1: How to do queries with LSI?

A: map query vectors into 'concept space' – how?

$$q = \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \\ \end{array}$$
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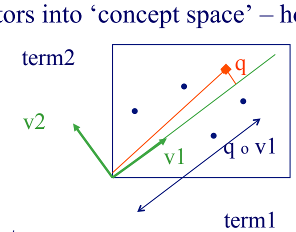

A: inner product (cosine similarity) with each 'concept' vector v_i

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Case study - LSI

compactly, we have:

$$q\,\mathbf{V} = q_{concept}$$

Eg:

$$q = \begin{array}{c} \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\ \begin{bmatrix} 1 & 0 & 0 & 0 & 0 \end{bmatrix} \end{array} \begin{bmatrix} 0.58 & 0 \\ 0.58 & 0 \\ 0.58 & 0 \\ 0 & 0.71 \\ 0 & 0.71 \end{bmatrix} = \begin{array}{c} \text{CS-concept} \\ \begin{bmatrix} 0.58 & 0 \end{bmatrix} \end{array}$$

term-to-concept similarities

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Case study - LSI

Drill: how would the document ('information', 'retrieval') be handled by LSI?

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Case study - LSI

Drill: how would the document ('information', 'retrieval') be handled by LSI? A: SAME:

$d_{concept} = d\,\mathbf{V}$

Eg:

$$d = \begin{array}{c} \begin{array}{ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} \end{array} \\ \begin{bmatrix} 0 & 1 & 1 & 0 & 0 \end{bmatrix} \end{array} \begin{bmatrix} 0.58 & 0 \\ 0.58 & 0 \\ 0.58 & 0 \\ 0 & 0.71 \\ 0 & 0.71 \end{bmatrix} = \begin{array}{c} \text{CS-concept} \\ \begin{bmatrix} 1.16 & 0 \end{bmatrix} \end{array}$$

term-to-concept similarities

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Case study - LSI

Observation: document ('information', 'retrieval') will be retrieved by query ('data'), although it does not contain 'data'!!

	data	inf.	retrieval	brain	lung		CS-concept	
d=	0	1	1	0	0	→	1.16	0
q=	1	0	0	0	0	→	0.58	0

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Case study - LSI

Q1: How to do queries with LSI?

Q2: multi-lingual IR (english query, on spanish text?)

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Case study - LSI

- Problem:
  - given many documents, translated to both languages (eg., English and Spanish)
  - answer queries across languages

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Case study - LSI

- Solution: ~ LSI

$$
\begin{array}{c|c}
 & \begin{array}{ccccc|ccccc} \text{data} & \text{inf.} & \text{retrieval} & \text{brain} & \text{lung} & \text{informacion} & \text{datos} & & & \end{array} \\
\begin{array}{c} \text{CS} \\ \\ \\ \\ \text{MD} \\ \\ \\ \end{array} &
\left[\begin{array}{ccccc|ccccc}
1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\
2 & 2 & 2 & 0 & 0 & 1 & 2 & 2 & 0 & 0 \\
1 & 1 & 1 & 0 & 0 & 1 & 1 & 1 & 0 & 0 \\
5 & 5 & 5 & 0 & 0 & 5 & 5 & 4 & 0 & 0 \\
0 & 0 & 0 & 2 & 2 & 0 & 0 & 0 & 2 & 2 \\
0 & 0 & 0 & 3 & 3 & 0 & 0 & 0 & 2 & 3 \\
0 & 0 & 0 & 1 & 1 & 0 & 0 & 0 & 1 & 1
\end{array}\right]
\end{array}
$$

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SVD - Case studies

- multi-lingual IR; LSI queries
- compression
- PCA - 'ratio rules'
- Karhunen-Lowe transform
- query feedbacks
- google/Kleinberg algorithms

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Case study: compression

[Korn+97]

Problem:

- given a matrix
- compress it, but maintain 'random access'

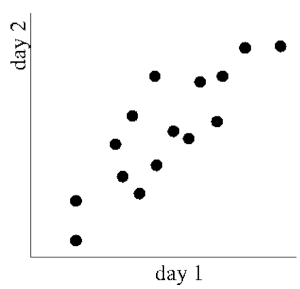
(surprisingly, its solution leads to data mining and visualization...)

Problem - specs

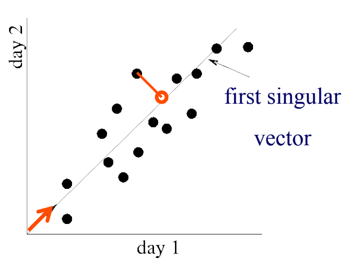
- ~10**6 rows; ~10**3 columns; no updates;
- random access to any cell(s) ; small error: OK

day customer	We 7/10/96	Th 7/11/96	Fr 7/12/96	Sa 7/13/96	Su 7/14/96
ABC Inc.	1	1	1	0	0
DEF Ltd.	2	2	2	0	0
GHI Inc.	1	1	1	0	0
KLM Co.	5	5	5	0	0
Smith	0	0	0	2	2
Johnson	0	0	0	3	3
Thompson	0	0	0	1	1

Idea



SVD - reminder



- space savings: 2:1
- minimum RMS error

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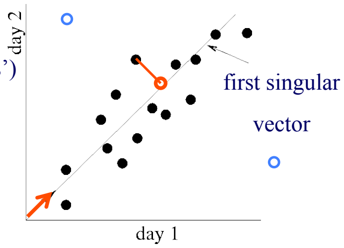
Case study: compression

outliers?
A: treat separately
(SVD with 'Deltas')



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Compression - Performance

- 3 pass algo (-> scalability) (HOW?)
- random cell(s) reconstruction
- 10:1 compression with < 2% error

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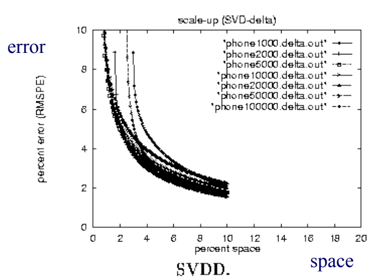
Performance - scaleup



SVDD.

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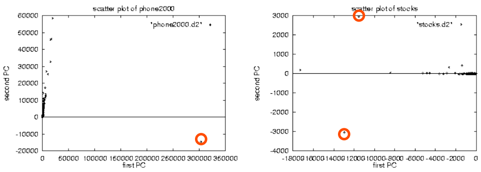
Compression - Visualization

- no Gaussian clusters; Zipf-like distribution



(a) 'phone2000' (b) 'stocks'

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SVD - Case studies

- multi-lingual IR; LSI queries
- compression
- PCA - 'ratio rules'
- Karhunen-Lowe transform
- query feedbacks
- google/Kleinberg algorithms

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PCA - 'Ratio Rules'

[Korn+00]

Typically: '*Association Rules'* (eg.,
{bread, milk} -> {butter}

But:

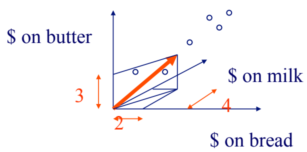
- which set of rules is 'better'?
- how to reconstruct missing/corrupted values?
- need binary/bucketized values

PCA - 'Ratio Rules'

Idea: try to find 'concepts':

- singular vectors dictate rules about ratios:

bread:milk:butter = 2:4:3



PCA - 'Ratio Rules'

Identical to PCA = Principal Components Analysis

- Q1: which set of rules is 'better'?
- Q2: how to reconstruct missing/corrupted values?
- Q3: is there need for binary/bucketized values?
- Q4: how to interpret the rules (= 'principal components')?

PCA - 'Ratio Rules'

Q2: how to reconstruct missing/corrupted values?

Eg:

- rule: bread:milk = 3:4
- a customer spent $6 on bread - how about milk?

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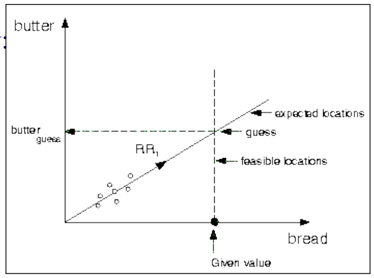
PCA - 'Ratio Rules'

pictorially:



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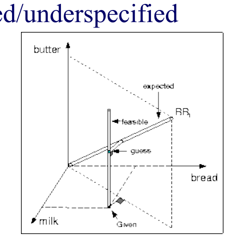
details

PCA - 'Ratio Rules'

harder cases: overspecified/underspecified

over-specified:
- milk:bread:butter = 1:2:3
- a customer got
  - $2 bread and $4 milk
- how much milk?

Answer: minimize distance between 'feasible' and 'expected' values (using SVD...)



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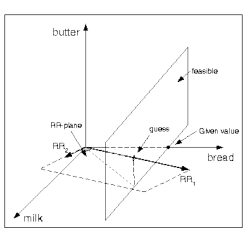
details

PCA - 'Ratio Rules'

harder cases: underspecified



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PCA - 'Ratio Rules'

bottom line: we can reconstruct any count of missing values

This is very useful:

- can spot outliers (how?)
- can measure the 'goodness' of a set of rules (how?)

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PCA - 'Ratio Rules'

Identical to PCA = Principal Components Analysis

- Q1: which set of rules is 'better'?
- √ Q2: how to reconstruct missing/corrupted values?
- Q3: is there need for binary/bucketized values?
- Q4: how to interpret the rules (= 'principal components')?

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PCA - 'Ratio Rules'

- Q1: which set of rules is 'better'?
- A: the ones that needs the fewest outliers:
  - pretend we don't know a value (eg., $ of 'Smith' on 'bread')
  - reconstruct it
  - and sum up the squared errors, for all our entries
- (other answers are also reasonable)

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PCA - 'Ratio Rules'

Identical to PCA = Principal Components Analysis

- √ – Q1: which set of rules is 'better'?
- √ – Q2: how to reconstruct missing/corrupted values?
- ➡ – Q3: is there need for binary/bucketized values?
- – Q4: how to interpret the rules (= 'principal components')?

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PCA - 'Ratio Rules'

Identical to PCA = Principal Components Analysis

- √ – Q1: which set of rules is 'better'?
- √ – Q2: how to reconstruct missing/corrupted values?
- √ – Q3: is there need for binary/bucketized values? NO
- ➡ – Q4: how to interpret the rules (= 'principal components')?

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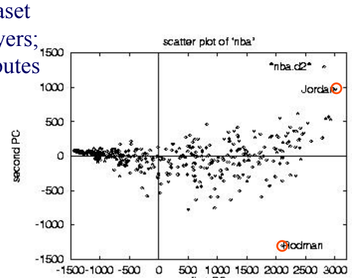
PCA - Ratio Rules

NBA dataset
~500 players;
~30 attributes



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PCA - Ratio Rules

- PCA: get singular vectors v1, v2, ...
- ignore entries with small abs. value
- try to interpret the rest

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PCA - Ratio Rules

NBA dataset - **V** matrix (term to 'concept' similarities)

field	RR_1	RR_2	RR_3
minutes played	.808	$-.4$	
field goals			
goal attempts			
points	.406	.199	
total rebounds		$-.489$	.602
assists			$-.486$
steals			$-.07$

v1

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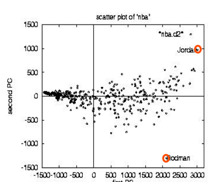
Ratio Rules - example

- RR1: minutes:points = 2:1
- corresponding concept?



v1

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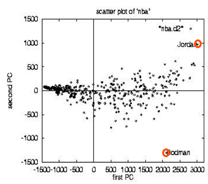
Ratio Rules - example

- RR1: minutes:points = 2:1
- co co



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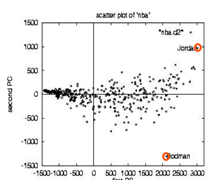
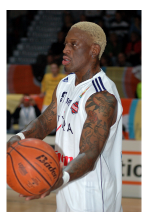
Ratio Rules - example

- RR1: minutes:points = 2:1
- co co



v1



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Ratio Rules - example

- RR1: minutes:points = 2:1
- corresponding concept?
- A: ‘goodness’ of player

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Ratio Rules - example

- RR2: points: rebounds negatively correlated (!)

field	RR_1	RR_2	RR_3
minutes played	.808	$-.4$	
field goals			
goal attempts			
points	.406	.199	
total rebounds		$-.489$	.602
assists			$-.486$
steals			$-.07$

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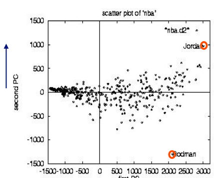
Ratio Rules - example

- RR2: points: rebounds negatively correlated (!) - concept?

v2



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Ratio Rules - example

- RR2: points: rebounds negatively correlated (!) - concept?
- A: position: offensive/defensive

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SVD - Case studies

- multi-lingual IR; LSI queries
- compression
- PCA - 'ratio rules'
- Karhunen-Lowe transform
- query feedbacks
- google/Kleinberg algorithms

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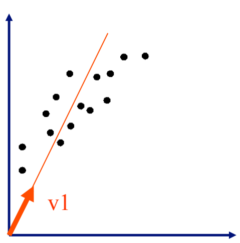
K-L transform



[Duda & Hart]; [Fukunaga]

A subtle point:
SVD will give vectors that go through the origin

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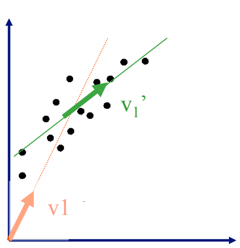
K-L transform



A subtle point:
SVD will give vectors that go through the origin
Q: how to find v_1' ?

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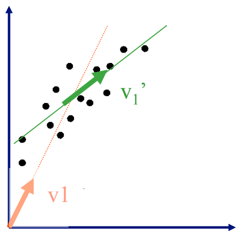
K-L transform



A subtle point:
SVD will give vectors that go through the origin
Q: how to find v_1’ ?

A: ‘centered’ PCA, ie., move the origin to center of gravity

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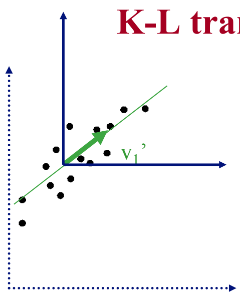
K-L transform



A subtle point:
SVD will give vectors that go through the origin
Q: how to find v_1’ ?

A: ‘centered’ PCA, ie., move the origin to center of gravity and THEN do SVD

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K-L transform

- How to ‘center’ a set of vectors (= data matrix)?
- What is the covariance matrix?
- A: see textbook
- (‘whitening transformation’)

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Conclusions

- SVD: popular for dimensionality reduction / compression
- SVD is the 'engine under the hood' for PCA (principal component analysis)
- ... as well as the Karhunen-Lowe transform
- (and there is more to come ...)

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