A few applications of the SVD

Many methods require to approximate the original data (matrix) by a low rank matrix before attempting to solve the original problem

➤ Regularization methods require the solution of a least-squares linear system $Ax = b$ approximately in the dominant singular space of A

➤ The Latent Semantic Indexing (LSI) method in information retrieval, performs the "query" in the dominant singular space of A

➤ Methods utilizing Principal Component Analysis, e.g. Face Recognition.

Commonality: Approximate A (or $A^\dagger$) by a lower rank approximation A_k (using dominant singular space) before solving original problem.

➤ This approximation captures the main features of the data while getting rid of noise and redundancy

Note: Common misconception: 'we need to reduce dimension in order to reduce computational cost'. In reality: using less information often yields better results. This is the problem of overfitting.

➤ Good illustration: Information Retrieval (IR)

Information Retrieval: Vector Space Model

➤   Given: a collection of documents (columns of a matrix A) and a query vector q.
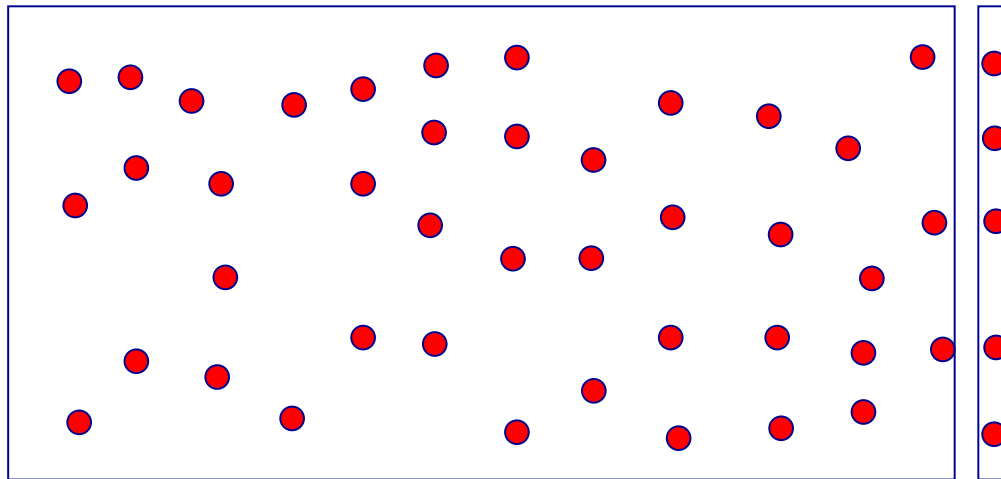
➤   Collection represented by an $m \times n$ term by document matrix with $\boxed{a_{ij} = L_{ij} G_i N_j}$

➤   Queries ('pseudo-documents') q are represented similarly to a column

Vector Space Model - continued

➤ Problem: find a column of A that best matches q

➤ Similarity metric: angle between the column and q - Use cosines:

$$\frac{|c^T q|}{\|c\|_2 \|q\|_2}$$

➤ To rank all documents we need to compute

$$s = A^T q$$

➤ $s = $ similarity vector.

➤ Literal matching – not very effective.

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Use of the SVD

➤ Many problems with literal matching: *polysemy*, *synonymy*, ...

➤ Need to extract intrinsic information – or underlying "semantic" information –

➤ Solution (LSI): replace matrix A by a low rank approximation using the Singular Value Decomposition (SVD)

$$A = U\Sigma V^T \quad \rightarrow \quad A_k = U_k\Sigma_k V_k^T$$

➤ U_k : term space, V_k: document space.

➤ Refer to this as Truncated SVD (TSVD) approach

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New similarity vector:

$$s_k = A_k^T q = V_k \Sigma_k U_k^T q$$

Issues:

➤ Problem 1: How to select k?

➤ Problem 2: computational cost (memory + computation)

➤ Problem 3: updates [e.g. google data changes all the time]

➤ Not practical for very large sets

LSI : an example

```
%% D1  :   INFANT & TODLER first aid
%% D2  :   BABIES & CHILDREN's room for your HOME
%% D3  :   CHILD SAFETY at HOME
%% D4  :   Your BABY's HEALTH and SAFETY
%%     :   From INFANT to TODDLER
%% D5  :   BABY PROOFING basics
%% D6  :   Your GUIDE to easy rust PROOFING
%% D7  :   Beanie BABIES collector's GUIDE
%% D8  :   SAFETY GUIDE for CHILD PROOFING your HOME
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
%% TERMS: 1:BABY  2:CHILD 3:GUIDE 4:HEALTH 5:HOME
%%        6:INFANT 7:PROOFING  8:SAFETY 9:TODDLER
%% Source: Berry and Browne, SIAM., '99
```

➤ Number of documents: 8

➤ Number of terms: 9

➤ Raw matrix (before scaling).

$$
A = \begin{array}{c|cccccccc|c}
 & d1 & d2 & d3 & d4 & d5 & d6 & d7 & d8 & \\
\hline
 & & 1 & & 1 & 1 & & 1 & & bab \\
 & 1 & 1 & & & & & & 1 & chi \\
 & & & & & & 1 & 1 & 1 & gui \\
 & & & & 1 & & & & & hea \\
 & & 1 & 1 & & & & & 1 & hom \\
 & 1 & & & 1 & & & & & inf \\
 & & & & & & 1 & 1 & 1 & pro \\
 & & & 1 & 1 & & & & 1 & saf \\
 & 1 & & & 1 & & & & & tod \\
\end{array}
$$

🖎$_1$ Get the anwser to the query `Child Safety`, so

$$q = [0\,1\,0\,0\,0\,0\,0\,1\,0]$$

using cosines and then using LSI with $k = 3$.

Dimension reduction

Dimensionality Reduction (DR) techniques pervasive to many applications

➤ Often main goal of dimension reduction is not to reduce computational cost. Instead:

- Dimension reduction used to reduce noise and redundancy in data
- Dimension reduction used to discover patterns (e.g., supervised learning)

➤ Techniques depend on desirable features or application: Preserve angles? Preserve distances? Maximize variance? ..

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The problem

➤ Given $d \ll m$ find a mapping
$$\Phi : x \ \in \mathbb{R}^m \longrightarrow y \ \in \mathbb{R}^d$$
➤ Mapping may be explicit (e.g.,
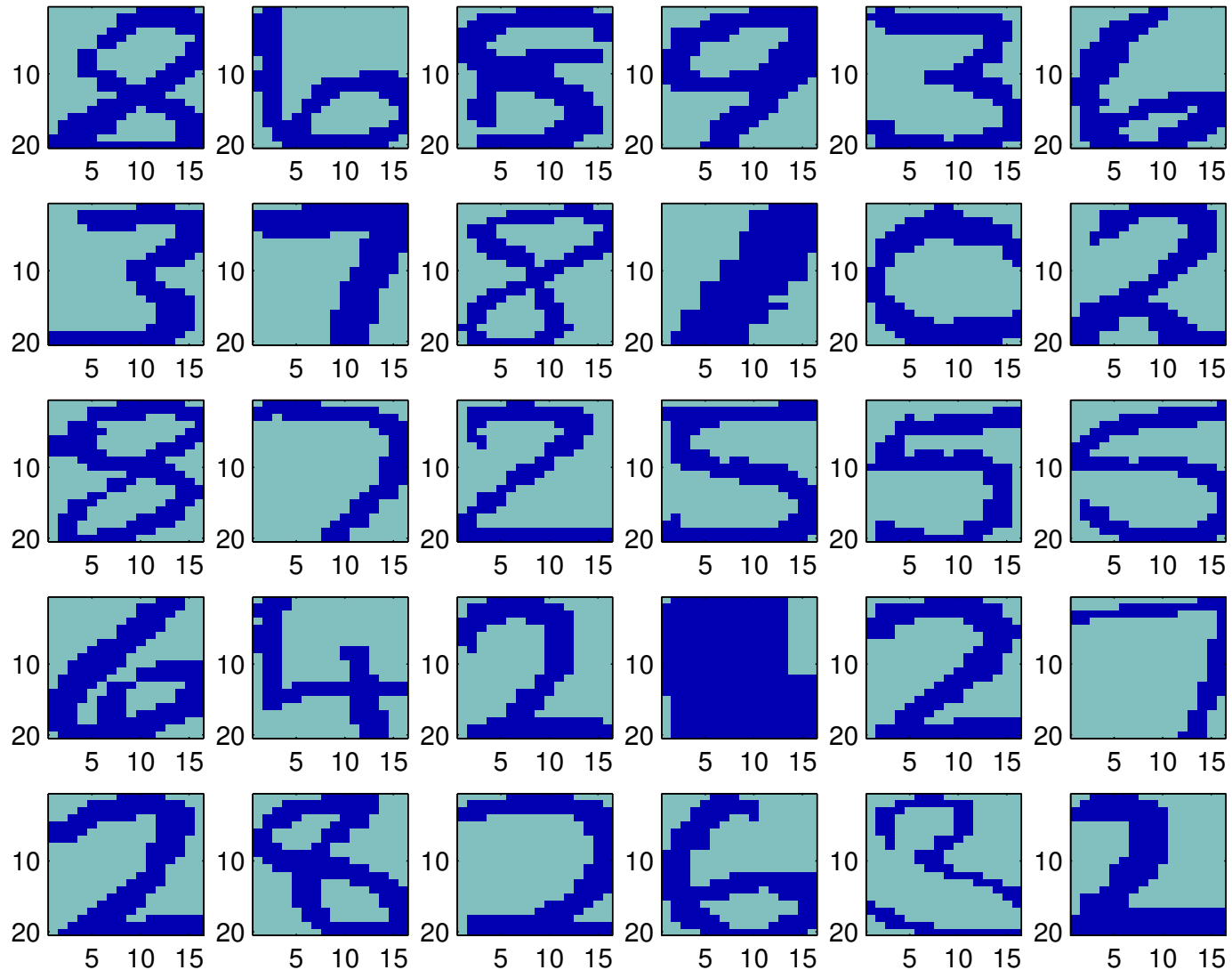$y = V^T x$)
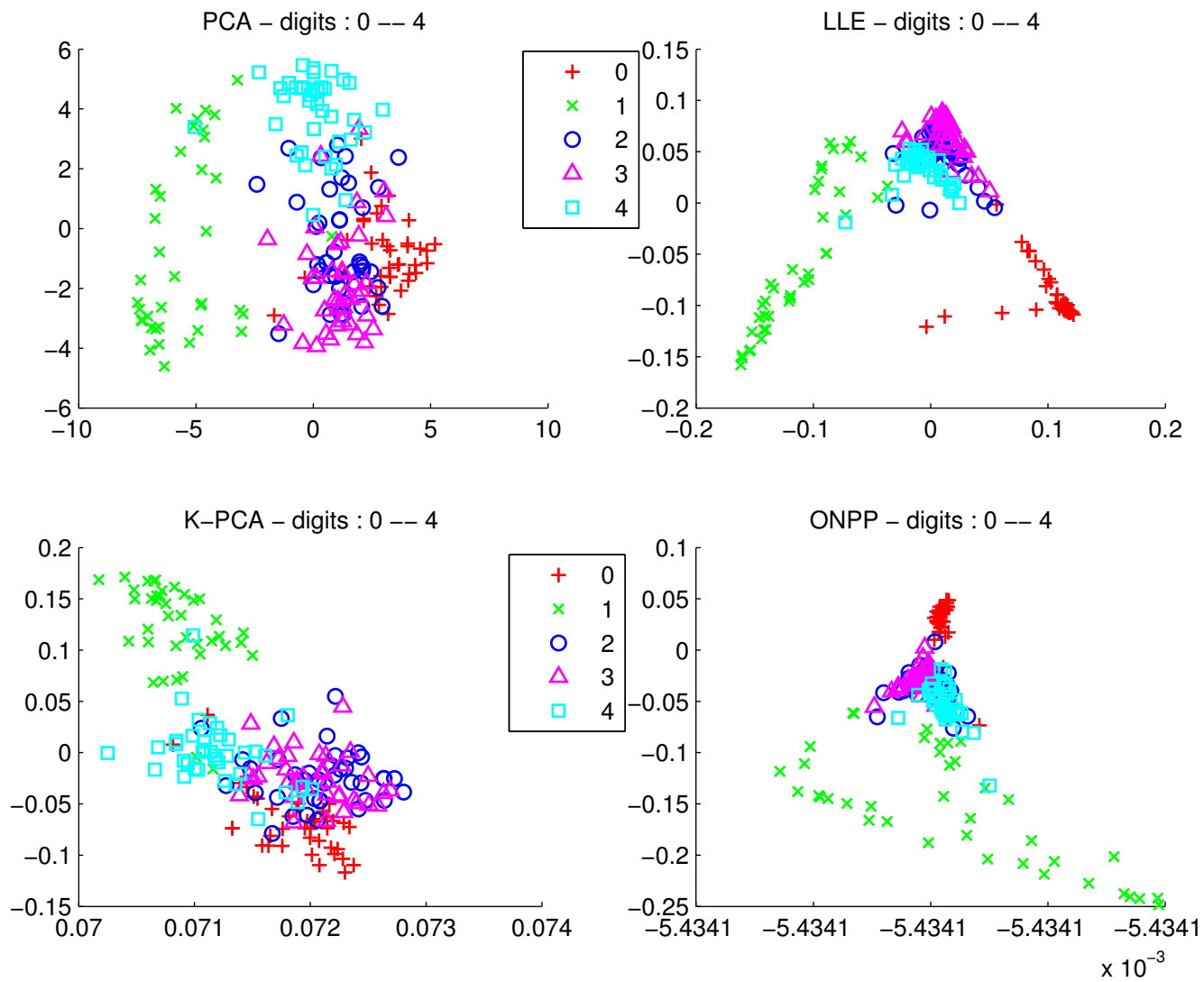➤ Or implicit (nonlinear)
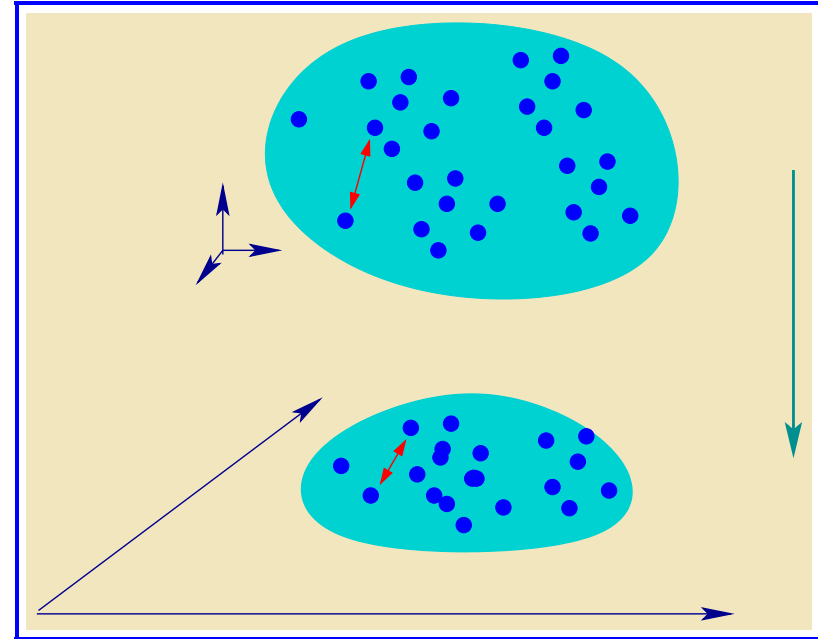
Practically: Find a low-dimensional representation $Y \ \in \mathbb{R}^{d \times n}$ of $X \ \in \mathbb{R}^{m \times n}$.

➤ Two classes of methods: (1) projection techniques and (2) nonlinear implicit methods.

A few 2-D 'reductions':

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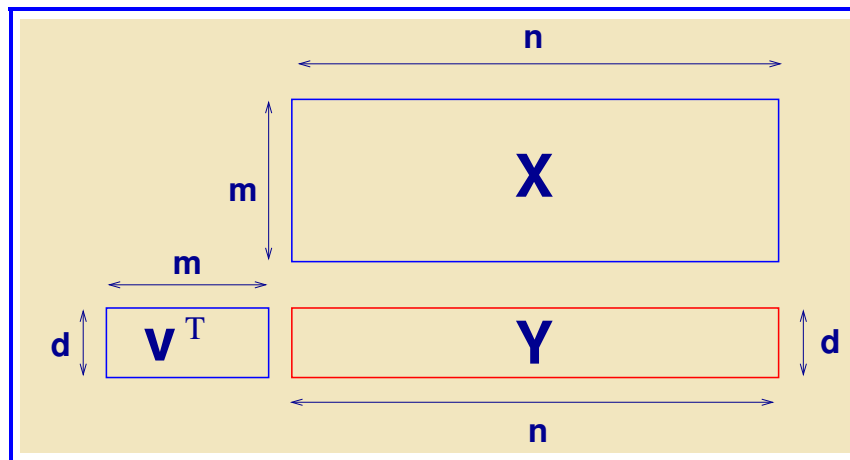# *Projection-based Dimensionality Reduction*

Given: a data set $X = [x_1, x_2, \ldots, x_n]$, and d the dimension of the desired reduced space Y.

Want: a linear transformation from X to Y

$$X \in \mathbb{R}^{m \times n}$$
$$V \in \mathbb{R}^{m \times d}$$
$$\boxed{Y = V^\top X}$$
$$\rightarrow \quad Y \in \mathbb{R}^{d \times n}$$

➤ m-dimens. objects (x_i) 'flattened' to d-dimens. space (y_i)

Problem: Find the best such mapping (optimization) given that the y_i's must satisfy certain constraints

Principal Component Analysis (PCA)

➤ PCA: find V (orthogonal) so that projected data $Y = V^T X$ has maximum variance

➤ Maximize over all orthogonal $m \times d$ matrices V:

$$\sum_i \| y_i - \frac{1}{n} \sum_j y_j \|_2^2 = \cdots = \mathsf{Tr} \left[V^\top \bar{X} \bar{X}^\top V \right]$$

Where: $\bar{X} = [\bar{x}_1, \cdots, \bar{x}_n]$ with $\bar{x}_i = x_i - \mu$, $\mu = $ mean.

Solution:

$V = \{$ dominant eigenvectors $\}$ of the covariance matrix

➤ i.e., Optimal $V = $ Set of left singular vectors of $\bar{X}$ associated with d largest singular values.

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✎2 Show that $\bar{X} = X(I - \frac{1}{n}ee^T)$ (here e = vector of all ones). What does the projector $(I - \frac{1}{n}ee^T)$ do?

✎3 Show that solution V also minimizes 'reconstruction error' ..

$$\sum_i \|\bar{x}_i - VV^T\bar{x}_i\|^2 = \sum_i \|\bar{x}_i - V\bar{y}_i\|^2$$

✎4 .. and that it also maximizes $\sum_{i,j} \|y_i - y_j\|^2$

Matrix Completion Problem

Consider a table of movie ratings. You want to predict missing ratings by assuming commonality (low rank matrix).

	given data			predictions		
movie	Paul	Jane	Ann	Paul	Jane	Ann
Title-1	−1	3	−1	−1.2	1.7	−0.7
Title-2	4	x	3	2.8	−1.2	2.5
Title-3	−3	1	−4	−2.7	1.0	−2.5
Title-4	x	−1	−1	−0.5	−0.3	−0.6
Title-5	3	−2	1	1.8	−1.4	1.4
Title-6	−2	3	x	−1.6	1.8	−1.2
	A			X		

➤ Minimize $\|(X - A)_{\mathrm{mask}}\|_F^2 + 4\|X\|_*$

"minimize sum-of-squares of deviations from known ratings plus sum of singular values of solution (to reduce the rank)."

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