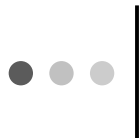


High-Dimensional Data



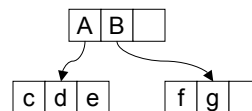
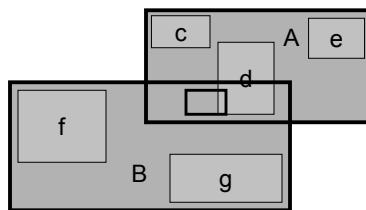
Topics

- Motivation
- Similarity Measures
- Index Structures



R trees, redux

- We want to minimize *coverage* and *overlap*

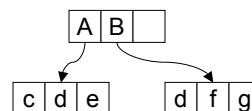
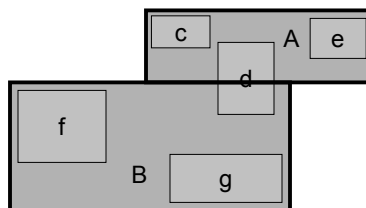


We descend both branches to search for



R+ Trees

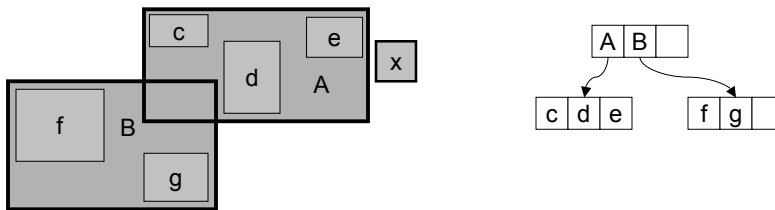
- store d in both A and B
- like splitting d into two pieces





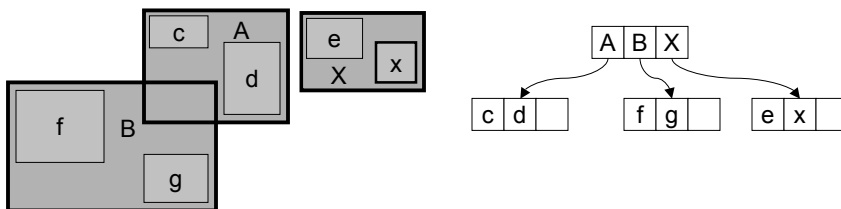
R* trees

- When a node overflows,
 - don't split it right away;
 - reinsert some of its nodes



R* trees

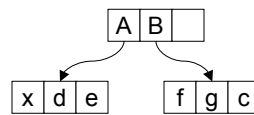
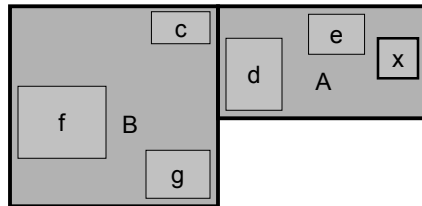
- Normal Insertion:



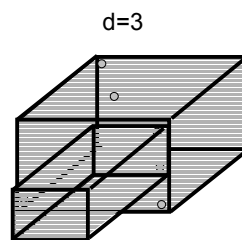
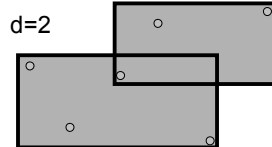


R* trees

- o Reinsert c instead of splitting node



Curse of Dimensionality



Coverage and overlap as a function of dimension?



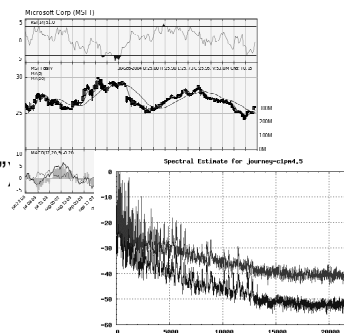
Curse of Dimensionality

- Generally: exponential growth of the hypervolume as a function of dimension
- Other manifestations:
 - number of samples required to maintain the same accuracy
 - number of nodes in a neural network required to “monitor” the input space
 - lots more



High-dimensional data

- Finance
- Multimedia
 - Sound
 - Music (“Query by humming”)
 - Images
 - Video
- Document Retrieval
- Biology/Medicine
 - DNA sequence matching
 - Medical imagery
- Moving Objects $[(t_0, x_0, y_0), (t_1, x_1, y_1), \dots]$
- High-Energy Physics





High-dimensional Access Methods

- Three components:
 - Similarity Measure
 - Index Structures
 - Search Strategy

we won't cover search strategy



Similarity Measure

- When are two vectors similar?

Q =



DB =





Similarity Measure

Define a function $s : V \rightarrow V \rightarrow \text{Real}$

What properties should s have?

Reflexive:

$$s(x,x) = 0 \text{ // or infinity}$$

Symmetric:

$$s(x,y) = s(y,x)$$

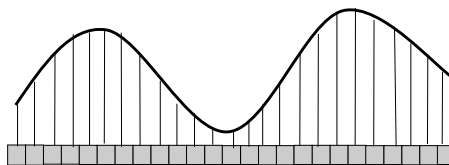
Triangle Inequality:

$$s(x,y) + s(y,z) \geq s(x,z)$$

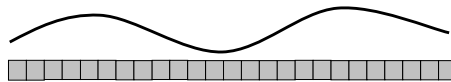


Timeseries Indexing

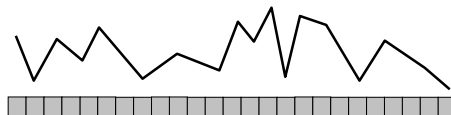
Q =



A =

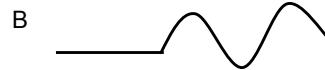
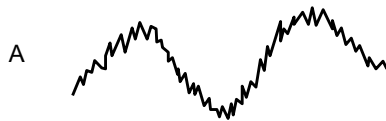
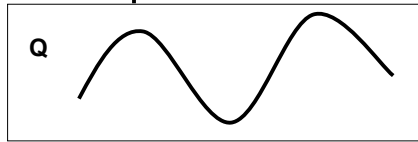


B =





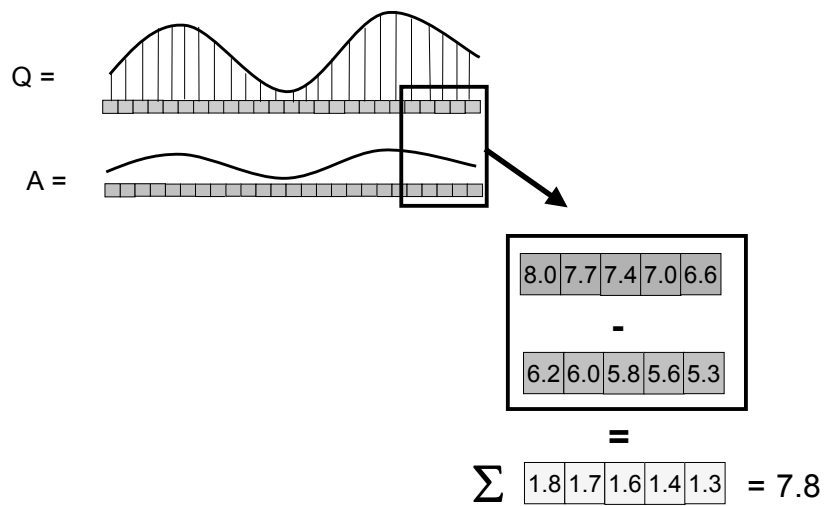
Timeseries Indexing



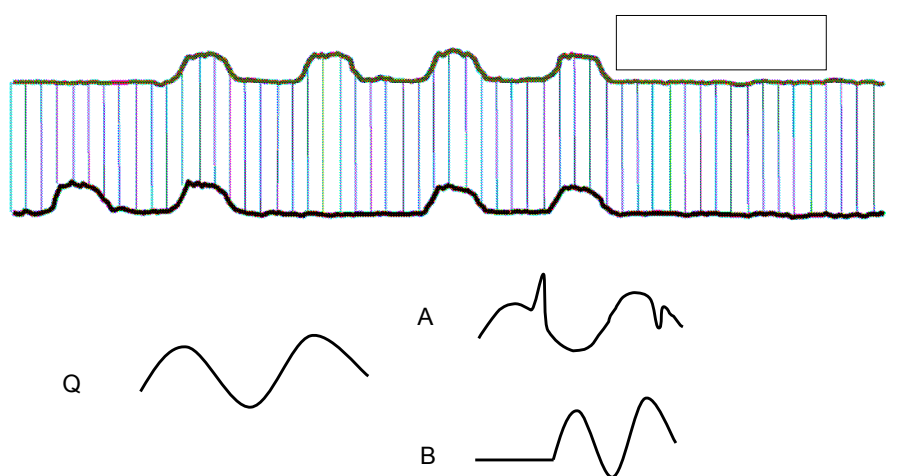
Timeseries Indexing

- Euclidean distance
- Dynamic Time Warping
 - Jagadish, Faloutsos 1998, Keogh 2002
- Wavelets
 - Miller 2003
- LCSS
 - Vlachos, Kollios, Gunopulos 2002
- EDR
 - Chen, Ozsu, Oria 2005

Euclidean Distance

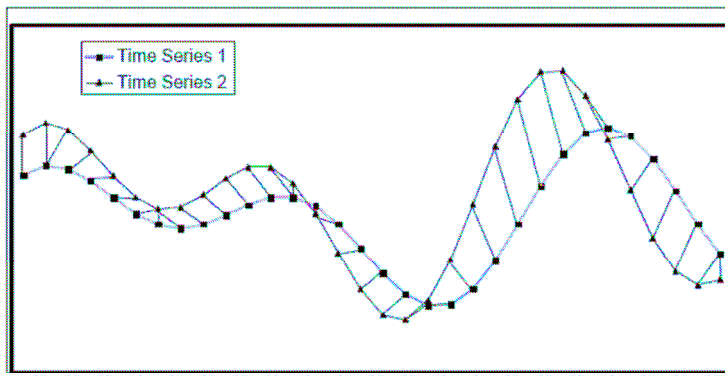


Euclidean Distance (2)





Dynamic Time Warping

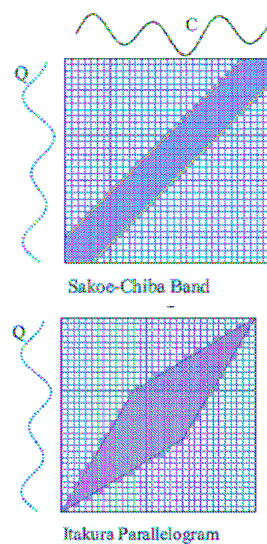
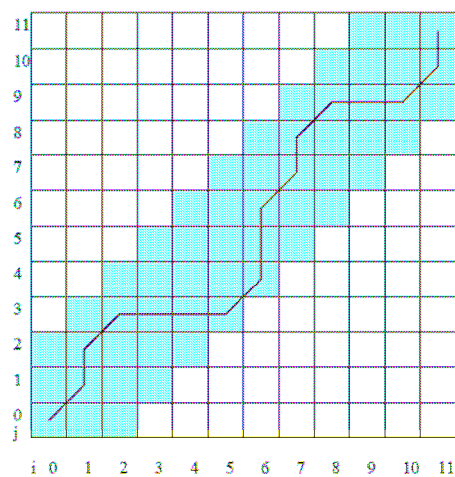


Dynamic Time Warping (2)

$$D_{DTW}^2(x, y) = D^2(\text{First}(x), \text{First}(y)) + \min \begin{cases} D_{DTW}^2(x, \text{Rest}(y)) \\ D_{DTW}^2(y, \text{Rest}(x)) \\ D_{DTW}^2(\text{Rest}(x), \text{Rest}(y)) \end{cases}$$

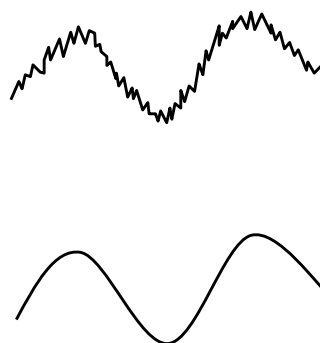


Dynamic Time Warping (3)

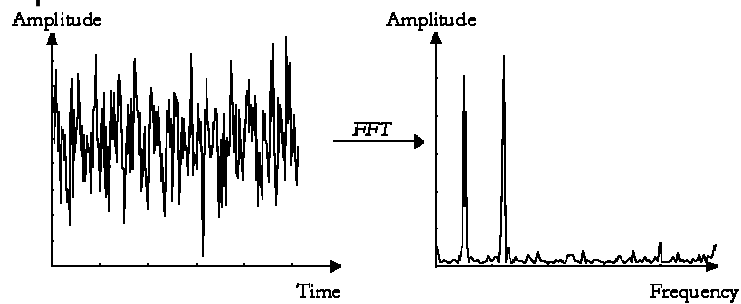


Dynamic Time Warping (4)

- Drawbacks:
 - Sensitive to noise
 - expensive to compute



Wavelets

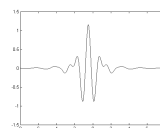
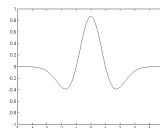
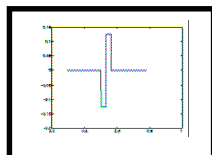
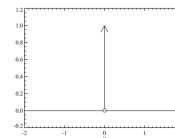
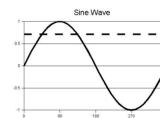


- Fourier Transform
 - Represents a timeseries as a sum of sine waves
 - The coefficients of the constituent waves indicate the dominant structure

Wavelets (2)

- Same trick, different basis function:

- Sum of sine waves?
- Sum of Dirac delta functions?
- Sum of ...





Wavelets (3)

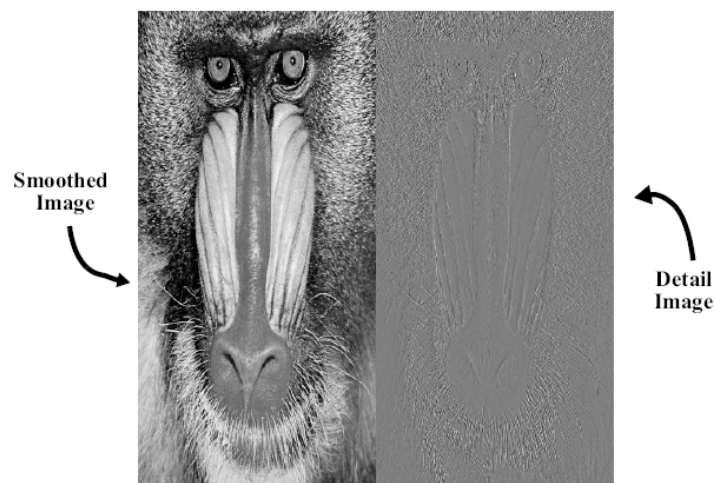
Haar wavelet transform

	Original Signal	2	7	11	8	11	5	0	3
$S_i + S_{i+1}$									
$S_i - S_{i+1}$	Detail Signal (1)	-5		3		6		-3	
	Detail Signal (2)	-10				13			
	Smoothed Signal (3)	47							
	Detail Signal (3)	9							

Hierarchical decomposition allows fine-tuning



Wavelets (4)

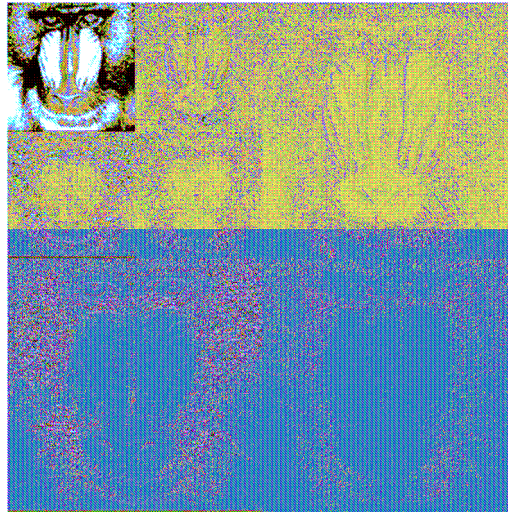


After one Horizontal filtering



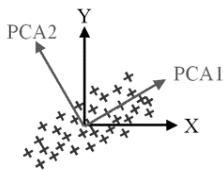
Wavelets (5)

- After two vertical and horizontal filterings



Wavelets (6)

- Wavelets can *reduce dimensionality*, like
 - Principal Component Analysis (PCA),
 - Singular Value Decomposition (SVD),
 - others



- Indexing in the reduced feature space
 - False positives ok, False negatives aren't
 - Use a more refined similarity measure to eliminate false positives



Other measures

o Longest Common Subsequence

$$LCSS(R, S) = \begin{cases} 0 & \text{if } m = 0 \text{ or } n = 0 \\ LCSS(Rest(R), Rest(S)) + 1 & \text{if } |r_{1,x} - s_{1,x}| \leq \epsilon \\ & \& |r_{1,y} - s_{1,y}| \leq \epsilon \\ \max\{LCSS(Rest(R), S), LCSS(R, Rest(S))\} & \text{otherwise} \end{cases}$$

o Edit Distance on Real sequence

$$EDR(R, S) = \begin{cases} n & \text{if } m = 0 \\ m & \text{if } n = 0 \\ \min\{EDR(Rest(R), Rest(S)) + subcost, \\ EDR(Rest(R), S) + 1, EDR(R, Rest(S)) + 1\} & \text{otherwise} \end{cases}$$

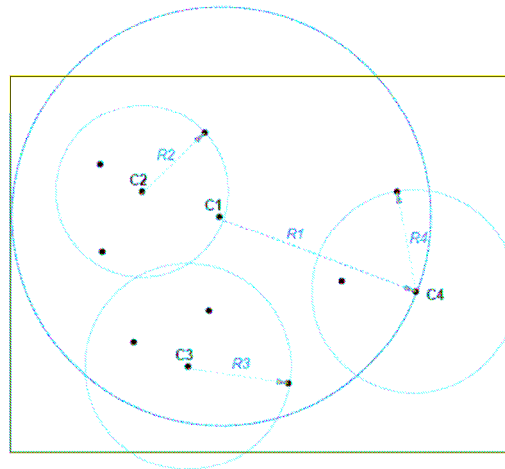


Index Structures

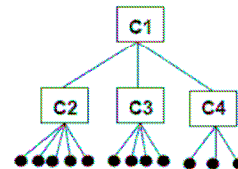
- o SS-Tree [White, Jain 96]
 - *R*-Tree using Minimum Bounding Spheres*
- ➡ o SR-Tree [Katayama, Satoh 97]
 - *Uses MBR during construction,*
 - *but MBS during lookup*
- o X-Tree [Berchtold, Kreim, Kriegel 96]
 - *R*-Tree using extended nodes to avoid splits and control maximum overlap*
- ➡ o M-Tree [Ciaccia, Patella 00]
 - *Build tree based on representative points*
- o TV-tree [Lin, Jagadish, Faloutsos 94]

SR-Tree and M-Tree appear to outperform others

M-Tree



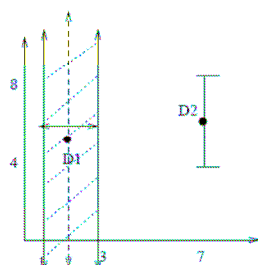
M-Tree partitioning of Ω_d



Associated M-Tree

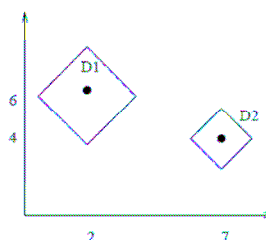
Telscoping Vector Tree (TV)

- node = (center, radius)
- $\dim(\text{center}) \geq \#$ of “active dimensions”



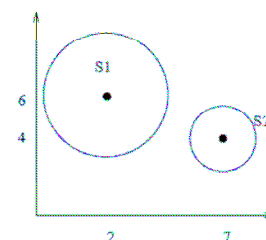
$D1$: Center (2) Radius 1
 $D2$: Center (7, 6) Radius 2

Number of active dimensions = 1



$D1$: Center (2,6) Radius 2
 $D2$: Center (7,4) Radius 1

Number of active dimensions = 2



$S1$: Center (2,6) Radius 2
 $S2$: Center (7,4) Radius 1

Number of active dimensions = 2