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15-826: Multimedia Databases and Data Mining

Lecture #30: Conclusions
C. Faloutsos

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Outline

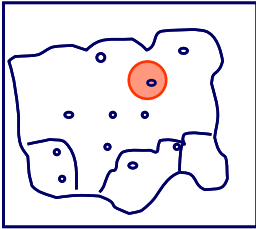
Goal: 'Find similar/ interesting things'

- Intro to DB
- Indexing - similarity search
 - Points
 - Text
 - Time sequences; images etc
 - Graphs

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Indexing - similarity search

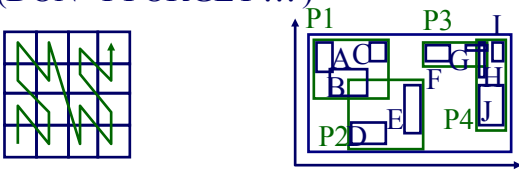


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Indexing - similarity search

- R-trees
- z-ordering/ hilbert curves
- M-trees
- (DON' T FORGET ...)



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Indexing - similarity search

- R-trees
- z-ordering / hilbert curves
- M-trees
- **beware of high intrinsic dimensionality**

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Text searching

- 'find all documents with word *bla*'

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Text searching

- Full text scanning ('grep')
- Inversion (B-tree or hash index)
- signature files – Bloom filters
- Vector space model
 - Ranked output
 - Relevance feedback
- String editing distance (-> dynamic prog.)

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Multimedia indexing

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'GEMINI' - Pictorially

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Multimedia indexing

- Feature extraction for indexing (GEMINI)
 - Lower-bounding lemma, to guarantee no false dismissals
- MDS/FastMap

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Time series & forecasting

Goal: given a signal (eg., sales over time and/or space)
 Find: patterns and/or compress

count
year

DFT

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Wavelets

- Q: baritone/silence/soprano - DWT?

f ↑

value

time

Signal

Scalogram

E1 E2 E3

f ↓

Level number

Scale of colour from MIN to MAX

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Time series + forecasting

- Fourier; Wavelets
- Box/Jenkins and AutoRegression
- non-linear/chaotic forecasting (fractals again)
 - ‘Delayed Coordinate Embedding’ ~ nearest neighbors

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Graphs


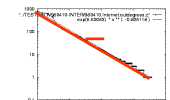
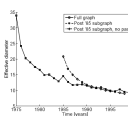
- Real graphs: surprising patterns
 - ??

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Graphs

- Real graphs: surprising patterns
 - 'six degrees'
 - **Skewed** degree distribution ('rich get richer')
 - Super-linearities (2x nodes -> 3x edges)
 - Diameter: **shrinks** (!)
 - Might have **no** good cuts

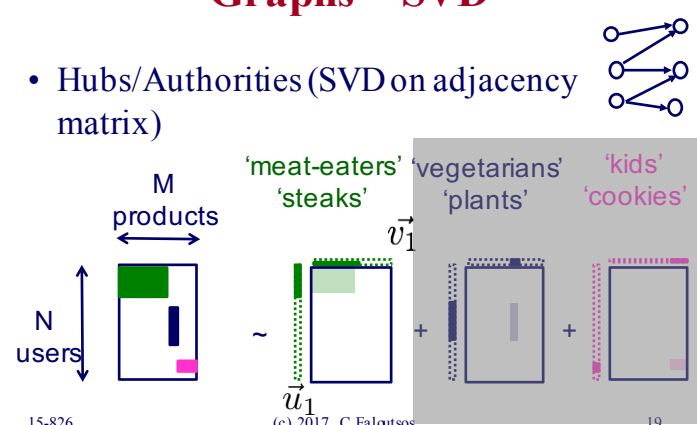




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Graphs - SVD

- Hubs/Authorities (SVD on adjacency matrix)

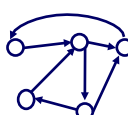
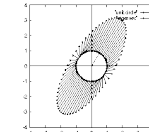


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Graphs - PageRank

- Hubs/Authorities (SVD on adjacency matrix)
- PageRank (fixed point -> eigenvector)

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Tensors

- Eg., time evolving graphs; Subject-verb-object triplets; etc

verb

subject

object

=

politicians

+

artists

+

athletes

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Taking a step back:

We saw some fundamental, recurring concepts and tools:

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T1: Powerful, recurring tools

- Fractals/ selfsimilarity

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T1: Powerful, recurring tools

- Fractals/ selfsimilarity <-> Power laws
 - Zipf, Korcak, Pareto's laws
 - intrinsic dimension (Sierpinski triangle)
 - correlation integral
 - Barnsley's IFS compression
 - Kronecker graphs

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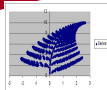
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T1: Powerful, recurring tools

- Fractals/ selfsimilarity
 - Zipf, K

• ‘Take logarithms’
• mean → meaningless
• Gaussian trap

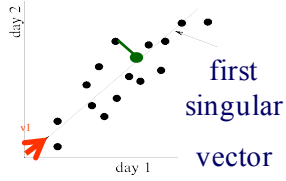


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T2: Powerful, recurring tools

- SVD (optimal L2 approx)

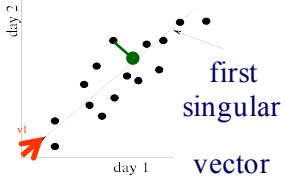


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T2: Powerful, recurring tools

- SVD (optimal L2 approx)
 - LSI, KL, PCA, ‘eigenSpokes’, (& in ICA)
 - HITS (PageRank)

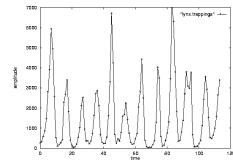


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T3: Powerful, recurring tools

- Discrete Fourier Transform
- Wavelets

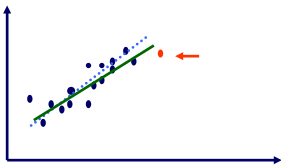


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T4: Powerful, recurring tools

- Matrix inversion lemma
 - Recursive Least Squares
 - Sherman-Morrison(-Woodbury)



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Summary

- **T1: fractals / power laws** lead to startling discoveries
 - ‘the mean may be meaningless’
 - Don’t assume Gaussian (average, k-means, etc)
- **T2: SVD**: behind PageRank/HITS/tensors/...
- **T3: Wavelets**: Nature seems to prefer them
- **T4: RLS**: matrix inversion, without inverting

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Thank you!

- Feel free to contact me:
 - Cell#; christos@cs; GHC 8019
- Reminder: faculty course eval’ s:
 - www.cmu.edu/hub/fce/
- Final: as announced in Hub
 - Mo 5/8/2017, 8:30-11:30am, DH 2315
 - (**double-check** with www.cmu.edu/hub/docs/final-exams.pdf)
- Have a great summer!



• ‘Take logarithms’
 • mean -> meaningless
 • Gaussian trap

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