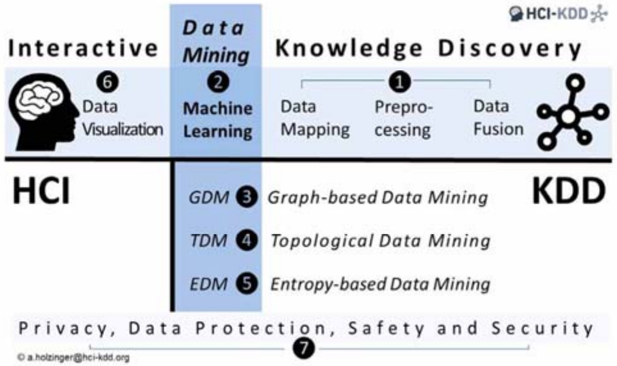
Science is to test crazy ideas – Engineering is to put these ideas into Business

Andreas Holzinger
VO 709.049 Medical Informatics
11.01.2017 11:15-12:45

Lecture 09 Interactive Visualization and Visual Analytics

a.holzinger@tugraz.at
Tutor: markus.plass@student.tugraz.at
http://hci-kdd.org/biomedical-informatics-big-data

Visualization is an essential part of Data Science



Keywords

- Data/Information/Knowledge visualization
- Flow cytometry
- Human-Computer Interaction (HCI)
- Information visualization
- Interactive information visualization
- k-Anonymization
- Longitudinal data
- Multivariate data
- Parallel coordinates
- RadViz
- Semiotics
- Star plots
- Temporal data analysis
- Visual analytics
- Visual information

Advance Organizer (1/2)

- **Biological data visualization** = as branch of bioinformatics concerned with visualization of sequences, genomes, alignments, phylogenies, macromolecular structures, systems biology, etc.
- **Clustering** = Mapping objects into disjoint subsets to let appear similar objects in the same subset;
- **Data visualization** = visual representation of complex data, to communicate information clearly and effectively, making data useful and usable;
- **Information visualization** = the interdisciplinary study of the visual representation of large-scale collections of non-numerical data, such as files and software, databases, networks etc., to allow users to see, explore, and understand information at once;
- **Multidimensional scaling** = Mapping objects into a low-dimensional space (plane, cube etc.) in order to let appear similar objects close to each other;
- **Multi-Dimensionality** = containing more than three dimensions and data are multivariate;
- **multivariate** = encompassing the simultaneous observation and analysis of more than one statistical variable; (Antonym: univariate = one-dimensional);

Advance Organizer (2/2)

- **Parallel Coordinates** = for visualizing high-dimensional and multivariate data in the form of N parallel lines, where a data point in the n-dimensional space is transferred to a polyline with vertices on the parallel axes;
- **RadViz** = radial visualization method, which maps a set of m-dimensional points in the 2-D space, similar to Hooke's law in mechanics;
- **Semiotics** = deals with the relationship between symbology and language, pragmatics and linguistics. Information and Communication Technology deals not only in words and pictures but also in ideas and symbology;
- **Semiotic engineering** = a process of creating a semiotic system, i.e. a model of human intelligence and knowledge and the logic for communication and cognition;
- **Star Plot** = aka radar chart, spider web diagram, star chart, polygon plot, polar chart, or Kiviat diagram, for displaying multivariate data in the form of a two-dimensional chart of three or more quantitative variables represented on axes starting from the same point;
- **Visual Analytics** = focuses on analytical reasoning of complex data facilitated by interactive visual interfaces;
- **Visualization** = a method of computer science to transform the symbolic into the geometric, to form a mental model and foster unexpected insights;

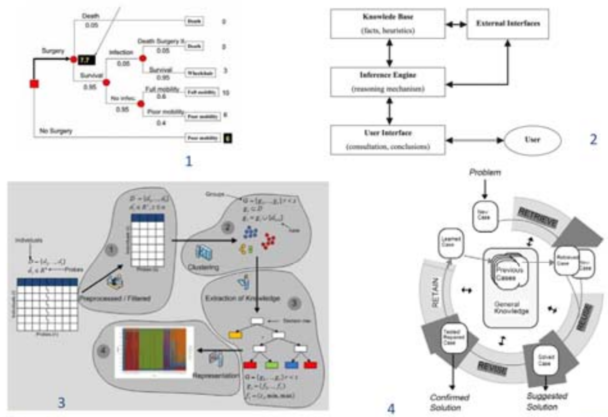
Learning Goals: At the end of this 9th lecture you ...

- ... have some background on visualization, visual analytics and content analytics;
- ... got an overview about various possible visualization methods for multivariate data;
- ... got an introduction into the work of and possibilities with parallel coordinates;
- ... have seen the principles of RadViz mappings and algorithms;
- ... are aware of the possibilities of Star Plots;
- ... have seen that visual analytics is intelligent Human-Computer Interaction at it finest;

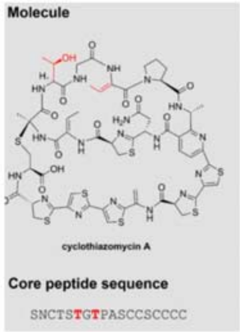
Agenda for today

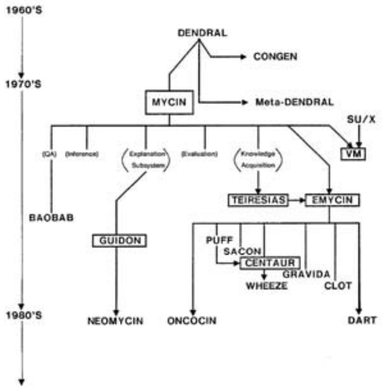
- 00 Reflection – follow-up from last lecture
- 01 Verbal vs. Visual Information
- 02 Informatics as Semiotics Engineering
- 03 Visualization Definitions
- 04 Usefulness of Visualization
- 05 Visualization Methods (long chapter but incomplete!)

Warm-up Quiz

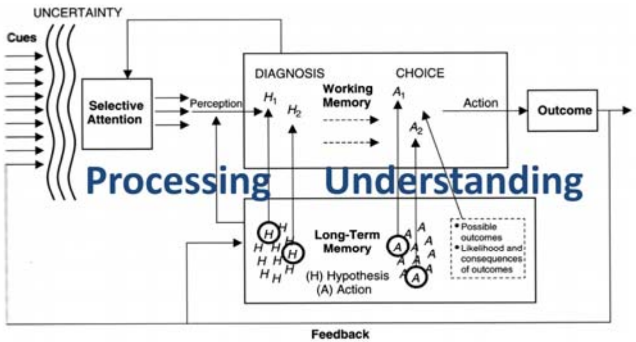


MYCIN – mother of …





Remember Slide 7-16 Human Decision Making



Wickens, C. D. (1984) *Engineering psychology and human performance. Columbus (OH), Charles Merrill.*

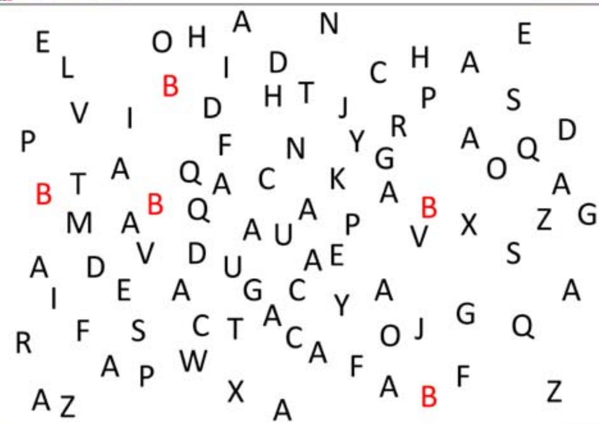
01 Verbal Information vs. Visual Information

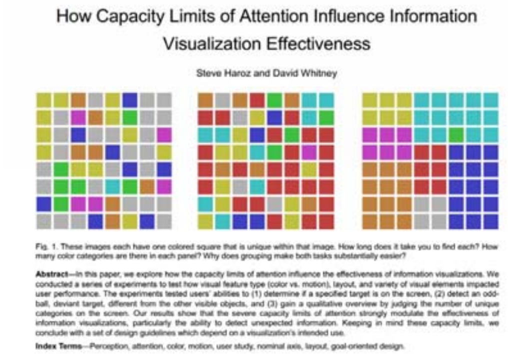
Slide 9-1 Key Challenges

- How to "visualize" high-dimensional spaces?
- The transformation of results from high-dimensional space $\mathbb{R}^N$ into $\mathbb{R}^2$
- From the complex to the simple (it is superhard to make it as simple as possible!)
- Sampling, modelling, rendering, perception, cognition, decision making … difficult!
- Trade-off between time and accuracy
- How to model uncertainty
- Integration of visual analytics techniques into the clinical workplace (integrative techniques): What is not in your **direct workflow** is ignored …

Please count all letters "B"

Is this easier?




How Capacity Limits of Attention Influence Information Visualization Effectiveness

Steve Haroz and David Whitney

Haroz, S. & Whitney, D. 2012. How capacity limits of attention influence information visualization effectiveness. IEEE Transactions on Visualization and Computer Graphics, 18, (12), 2402-2410.

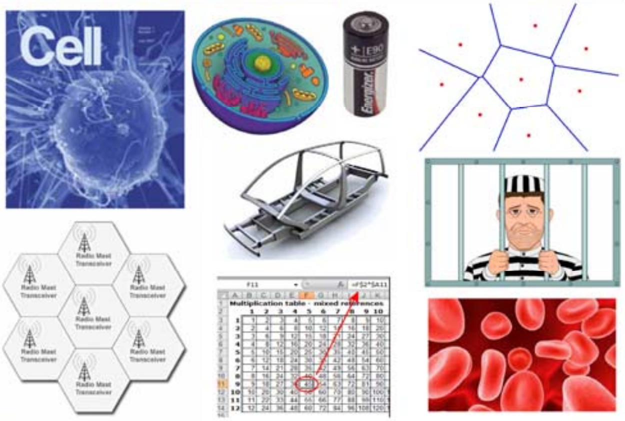
Limited Perceptual Capacity of Human Sensory Channels

https://www.youtube.com/watch?v=vJG698U2Mvo

Simons, D. J. & Chabris, C. F. 1999. Gorillas in our midst: sustained inattentional blindness for dynamic events. Perception, 28, (9), 1059-1074.

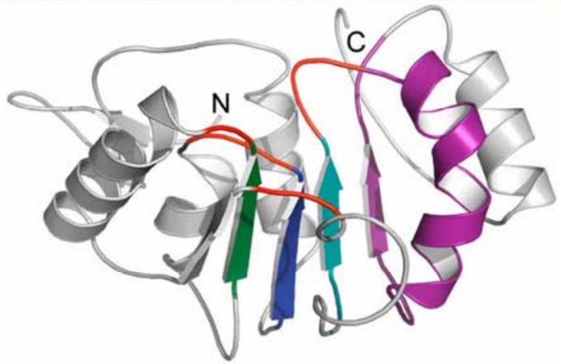
Problem: Context!

Semantic Ambiguity – Missing Context



A picture is worth a thousand words?

Slide 9-7: Example: Ribbon Diagram of a Protein Structure



Magnani, R., et al. 2010. Calmodulin methyltransferase is an evolutionarily conserved enzyme that trimethylates Lys-115 in calmodulin. *Nature Communications, 1, 43.*

Slide 9-8 "Is a picture really worth a thousand words?"

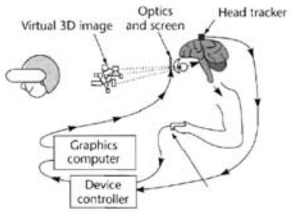
02 Informatics as Semiotics Engineering

Slide 9-9 Three examples for Visual Languages

Ware, C. (2004) *Information Visualization: Perception for Design (Interactive Technologies) 2nd Edition. San Francisco, Morgan Kaufmann.*

$$W = \{w : w \in T(v)\}$$

$$H = -\sum_{w \in W} p(w) \log_2 p(w)$$



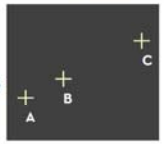
Holzinger, A., Searle, G., Auinger, A. & Ziefle, M. (2011) Informatics as Semiotics Engineering: Lessons learned from Design, Development and Evaluation of Ambient Assisted Living Applications for Elderly People. *Universal Access in Human-Computer Interaction. Context Diversity. Lecture Notes in Computer Science (LNCS 6767). Berlin, Heidelberg, New York, Springer, 183-192.*

Slide 9-10 Informatics as Semiotics Engineering

- 1. Physical: is it present?
  - Signals, traces, components, points, …
- 2. Empirical: can it be seen?
  - Patterns, entropy, codes, …
- 3. Syntactic: can it be read?
  - Formal structure, logic, deduction, …
- 4. Semantic: can it be understood?
  - Meaning, proposition, truth, …
- 5. Pragmatic: is it useful?
  - Intentions, negotiations, communications, …
- 6. Social: can it be trusted?
  - Beliefs, expectations, culture, …

Burton-Jones, A., Storey, V. C., Sugumaran, V. & Ahluwalia, P. 2005. A semiotic metrics suite for assessing the quality of ontologies. *Data & Knowledge Engineering, 55, (1), 84-102.*

Visual Language is a Sign System



- Images are perceived as a set of signs
- Sender **encodes** information in signs
- Receiver **decodes** information from signs
- *"Resemblance, order and proportion are the 3 "signifieds" in graphics"*
- *"With up to three rows, a data table can be constructed directly as a single image … However, an image has 3 dimensions And this barrier is impassible."*

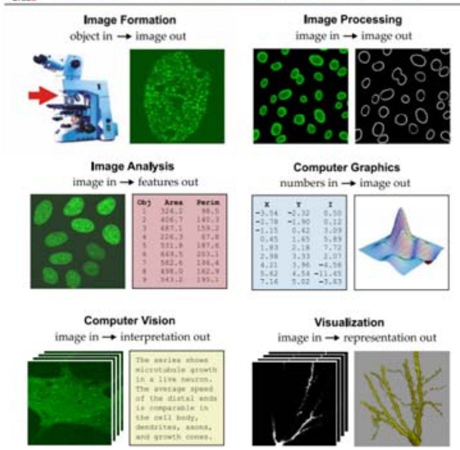
Bertin, J. & Barbut, M. 1967. Sémiologie graphique: les diagrammes, les réseaux, les cartes, Mouton Paris.

03 What is Visualization?

Slide 9-11 Definitions of the term "Visualization"

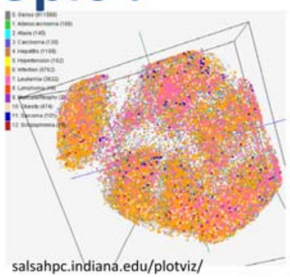
- **Visualization** = generally a method of computer science to **transform the symbolic into the geometric**, to form a mental model and foster unexpected insights;
- **Information visualization** = the interdisciplinary study of the visual representation of large-scale collections of non-numerical data, such as files and software, databases, networks etc., to allow users to see, explore, and understand information at once;
- **Data visualization** = visual representation of complex data, to communicate information clearly and effectively, making data useful and usable;
- **Visual Analytics** = focuses on analytical reasoning of complex data facilitated by **interactive** visual interfaces;
- **Content Analytics** = a general term addressing so-called "unstructured" information – mainly text – by using mixed methods from visual analytics and business intelligence;

Do *not* mix up Image Processing with Visualization



Meijering, Erik & Cappellen, Gert (2006) Biological Image Analysis Primer, available via http://www.imagescience.org/meijering/publications/1009/ Erasmus University Medical Center

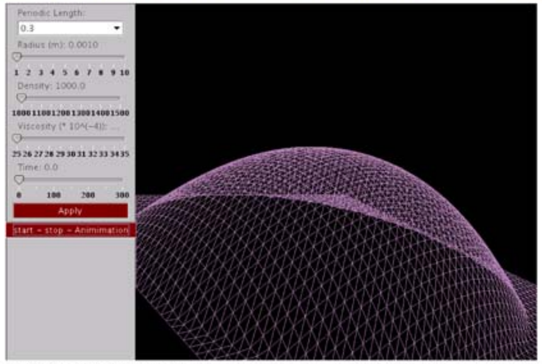
Visualization is a typical HCI topic !



Jong Youl Choi, Seung-Hee Bae, Judy Qiu, Geoffrey Fox, Bin Chen, and David Wild, "Browsing Large Scale Cheminformatics Data with Dimension Reduction," Proceedings of Emerging Computational Methods for the Life Sciences Workshop of ACM HPDC 2010 conference, Chicago, Illinois, June 20-25, 2010.

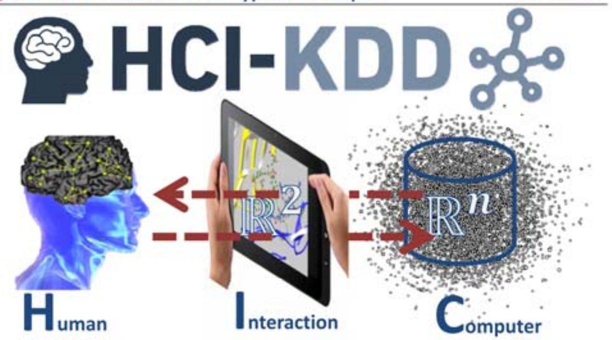
salsahpc.indiana.edu/plotviz/

Slide 9-12 Process of interactive (data) visualization



Holzinger, A., Kickmeier-Rust, M. D., Wassertheurer, S. & Hessinger, M. (2009) Learning performance with interactive simulations in medical education: Lessons learned from results of learning complex physiological models with the HAEMOdynamics SIMulator. *Computers & Education, 52, 2, 292-301.*

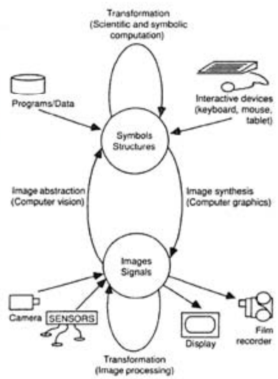
Slide 9-13 Visualization is a typical HCI topic!



Holzinger, A. 2013. Human–Computer Interaction & Knowledge Discovery (HCI-KDD): What is the benefit of bringing those two fields to work together? *In: Alfredo Cuzzocrea, C. K., Dimitris E. Simos, Edgar Weippl, Lida Xu (ed.) Multidisciplinary Research and Practice for Information Systems, Springer Lecture Notes in Computer Science LNCS 8127. Heidelberg, Berlin, New York: Springer, pp. 319-328.*

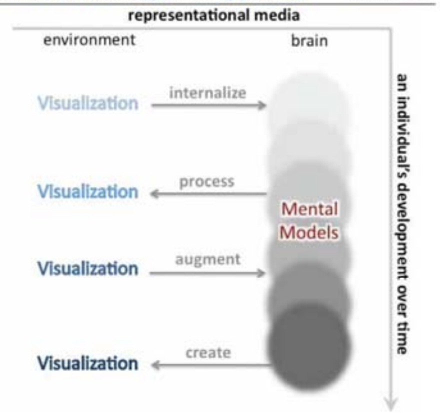
Slide 9-14 We can conclude that Visualization is …

- … the common denominator of Computational sciences
- … the transformation of the symbolic into the geometric
- … the support of human perception
- … facilitating knowledge discovery in data



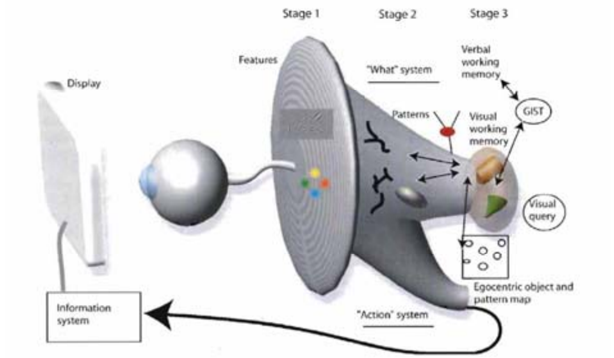
McCormick, B. (1987) Scientific and Engineering Research Opportunities. *Computer graphics, 21, 6.*

Slide 9-15 Visualization as an knowledge eliciting process



Liu, Z. & Stasko, J. T. (2010) Mental Models, Visual Reasoning and Interaction in Information Visualization: A Top-down Perspective. *Visualization and Computer Graphics, IEEE Transactions on, 16, 6, 999-1008.*

Slide 9-16 Model of Perceptual Visual Processing

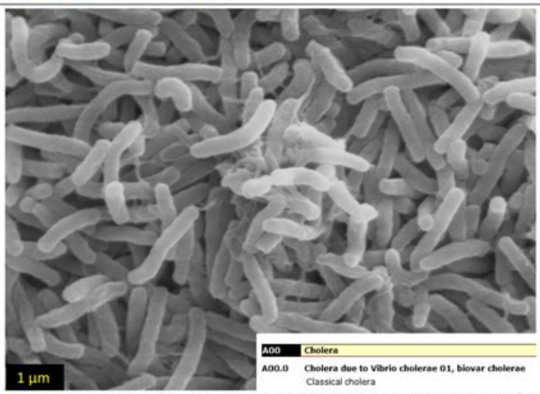


Ware, C. (2004) *Information Visualization: Perception for Design (Interactive Technologies) 2nd Edition. San Francisco, Morgan Kaufmann.*

04 Usefulness of Visualization Science

Slide 9-17 A look back into history …

What do you see in this picture?



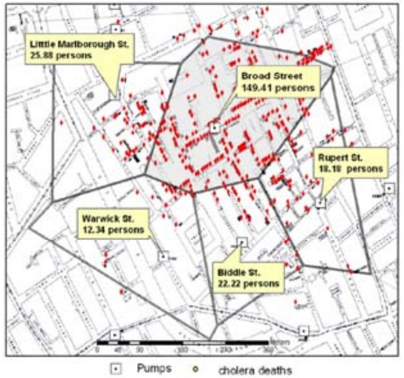
T.J. Kirn, M.J. Lafferty, C.M.P Sandoe and R.K. Taylor (2000) Delineation of pilin domains required for bacterial association into microcolonies and intestinal colonization, Molecular Microbiology, Vol. 35, 896-910

Slide 9-18 Medical Visualization by John Snow (1854)

McLeod, K. S. (2000) Our sense of Snow: the myth of John Snow in medical geography. *Social Science & Medicine, 50, 7-8, 923-935.*

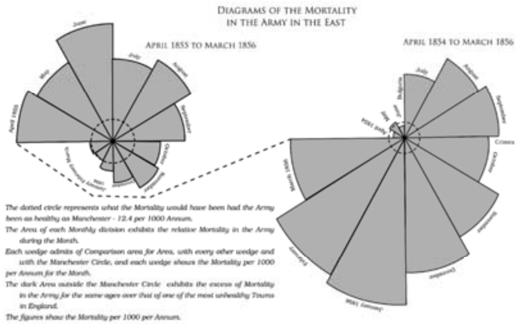
Slide 9-19 Systematic Visual Analytics > Content Analytics

Cholera Mortality per 1,000 persons



Koch, T. & Denike, K. (2009) Crediting his critics' concerns: Remaking John Snow's map of Broad Street cholera, 1854. *Social Science & Medicine, 69, 8, 1246-1251.*

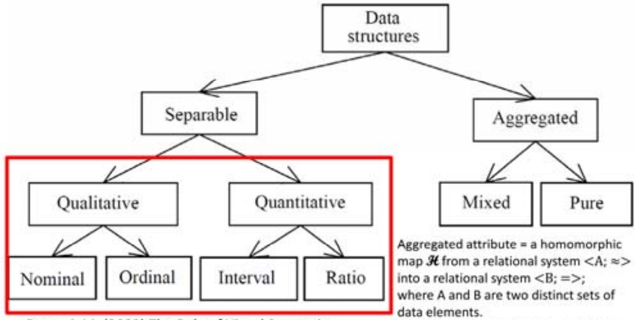
Florence Nightingale – first medical quality manager



Meyer, B. C. & Bishop, D. S. (2007) Florence Nightingale: nineteenth century apostle of quality. *Journal of Management History, 13, 3, 240-254.*

05 Visualization Basics

Example: Data structures - Classification



Aggregated attribute = a homomorphic map $\mathcal{H}$ from a relational system <A; ≈> into a relational system <B; =>; where A and B are two distinct sets of data elements. This is in contrast with other attributes since the set B is the set of data elements instead of atomic values.

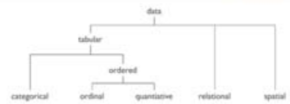
Dastani, M. (2002) The Role of Visual Perception in Data Visualization. *Journal of Visual Languages and Computing, 13, 601-622.*

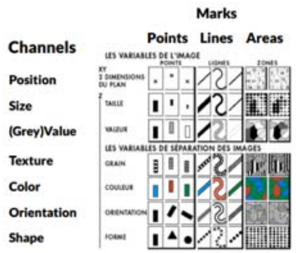
Slide 2-15: Categorization of Data (Classic "scales")

Scale	Empirical Operation	Mathem. Group Structure	Transf. in ℝ	Basic Statistics	Mathematical Operations
NOMINAL	Determination of equality	Permutation $x' = f(x)$ x … 1-to-1	$x \mapsto f(x)$	Mode, contingency correlation	=, ≠
ORDINAL	Determination of more/less	Isotonic $x' = f(x)$ x … mono-tonic incr.	$x \mapsto f(x)$	Median, Percentiles	=, ≠, >, <
INTERVAL	Determination of equality of intervals or differences	General linear $x' = ax + b$	$x \mapsto rx+s$	Mean, Std.Dev. Rank-Order Corr., Prod.-Moment Corr.	=, ≠, >, <, -, +
RATIO	Determination of equality or ratios	Similarity $x' = ax$	$x \mapsto rx$	Coefficient of variation	=, ≠, >, <, -, +, *, ÷

Stevens, S. S. (1946) On the theory of scales of measurement. *Science, 103, 677-680.*

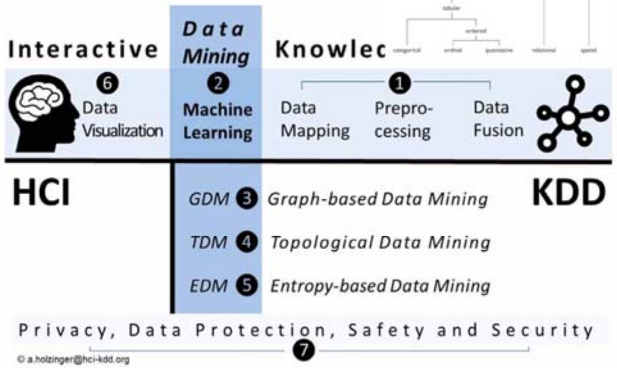
Remember Data structures





Bertin, J. & Barbut, M. 1967. Sémiologie graphique: les diagrammes, les réseaux, les cartes, Mouton Paris.

From abstract data to human perceivable information



The higher the dimensions the more analytics we need!

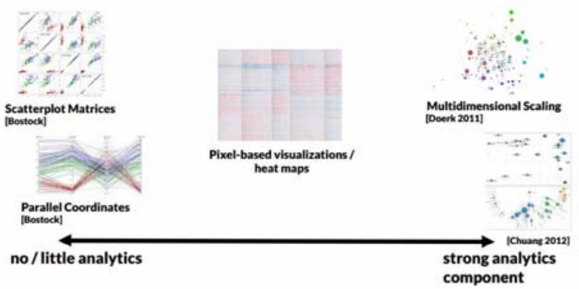
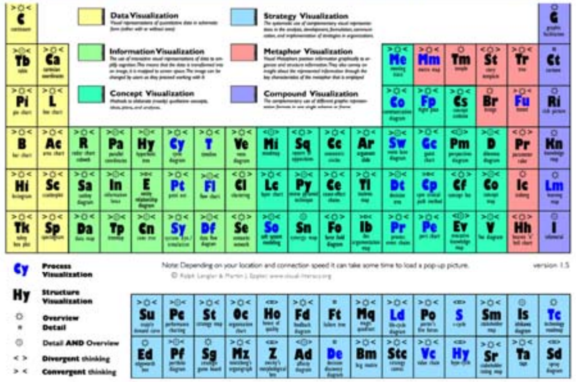


Image credit to Alexander Lex, Harvard

Example Chuang (2012) Dissertation Browser:
http://www-nlp.stanford.edu/projects/dissertations/browser.html

05 Visualization Methods (Incomplete!)

Slide 9-20 A periodic table of visualization methods

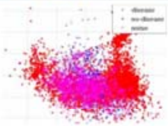


Lengler, R. & Eppler, M. J. (2007) Towards a periodic table of visualization methods for management. *Proceedings of Graphics and Visualization in Engineering (GVE 2007)*; Online: www.visual-literacy.org

Slide 9-21: A taxonomy of Visualization Methods

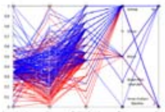
- 1) Data Visualization (Pie Charts, Area Charts or Line Graphs, …
- 2) Information Visualization (Semantic networks, tree-maps, radar-chart, …)
- 3) Concept Visualization (Concept map, Gantt chart, PERT diagram, …)
- 3) Metaphor Visualization (Metro maps, story template, iceberg, …)
- 4) Strategy Visualization (Strategy Canvas, roadmap, morpho box,…)
- 5) Compound Visualization

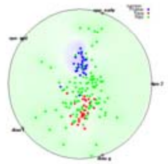
Slide 9-22 Visualizations for multivariate data Overview 1/2



Scatterplot = oldest, point-based technique, projects data from n-dim space to an arbitrary k-dim display space;

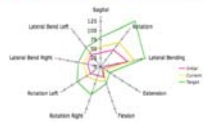
Parallel coordinates = (PCP), originally for the study of high-dimensional geometry, data point plotted as polyline;





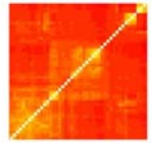
RadViz = Radial Coordinate visualization, is a "force-driven" point layout technique, based on Hooke's law for equilibrium;

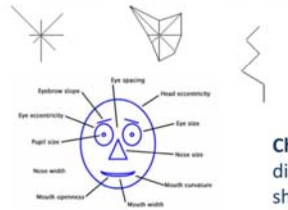
Slide 9-23 Visualizations for multivariate data Overview 2/2



Radar chart (star plot, spider web, polar graph, polygon plot) = radial axis technique;

Heatmap = a tabular display technique using color instead of figures for the entries;





Glyph = a visual representation of the entity, where its attributes are controlled by data attributes;

Chernoff face = a face glyph which displays multivariate data in the shape of a human face

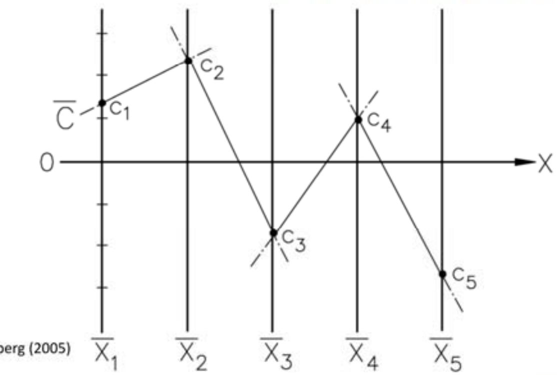
Slide 9-24 Parallel Coordinates – multidim. Visualization

- On the plane with Cartesian-coords, a vertical line, labeled $\bar{X}_i$ is placed at each $x = i - 1$ for $i = 1, 2, \dots N$.
- These are the axes of the parallel coordinate system for $\mathbb{R}^N$.
- A point $C = (c_1, c_2, \dots c_N) \in \mathbb{R}^N$ is mapped into the polygonal line $\bar{C}$
- the *N*-vertices with *xy-coords* $(i - 1, c_i)$ are now on the parallel axes.
- In $\bar{C}$ the full lines and not only the segments between the axes are included.

Inselberg, A. (2005) Visualization of concept formation and learning. *Kybernetes: The International Journal of Systems and Cybernetics, 34, 1/2, 151-166.*

Slide 9-25 Polygonal line $\bar{C}$ is representing a single point

$\mathbb{R}^5$: $C = (c_1, c_2, c_3, c_4, c_5)$

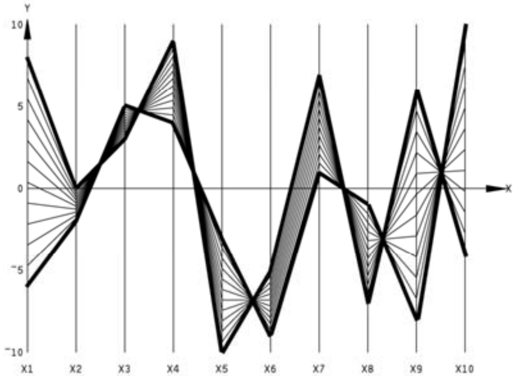


Inselberg (2005)

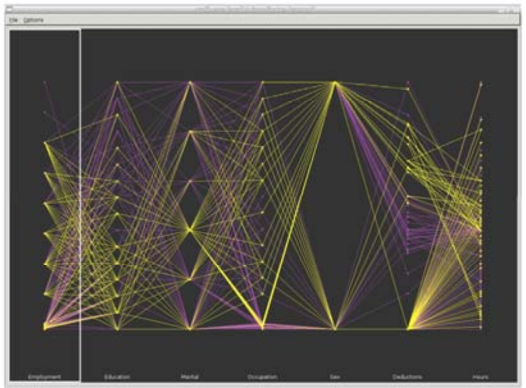
Slide 9-26 Heavier polygonal lines represent end-points

- A polygonal line $\bar{P}$ on the $N-1$ points represents a point
- $P = (p_1, \dots p_{i-1}, p_i \dots p_N) \in \ell$
- since the pair of values $\dots p_{i-1}, p_i$ marked on the $\bar{X}_{i-1}$ and $\bar{X}_i$ axes.
- In the following slide we see several polygonal lines, intersecting at $\ell_{(i-1),i}$
- representing data points on a line $\ell \subset \mathbb{R}^{10}$.
- Note: The indexing is essential and is important for the visualization of proximity properties such as the minimum distance between a pair of lines.

Slide 9-27 Line Interval in $\mathbb{R}^{10}$

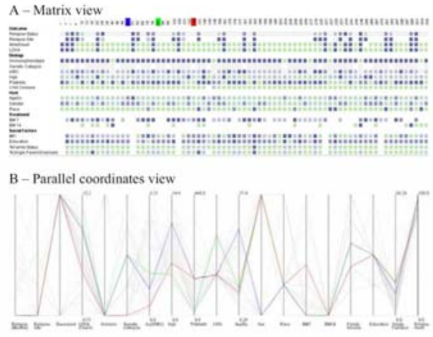


Slide 9-28 Example: Par Coords in a Vis Software in R



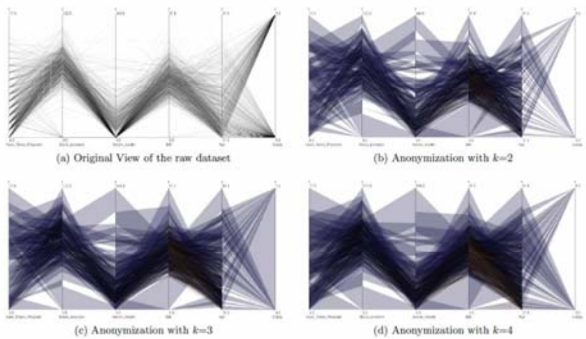
http://datamining.togaware.com

Slide 9-29 Par Coords -> Knowledge Discovery in big data



Mane, K. K. & Börner, K. (2007) Computational Diagnostic: A Novel Approach to View Medical Data. Los Alamos National Laboratory.

Slide 9-30 Ensuring Data Protection with k-Anonymization

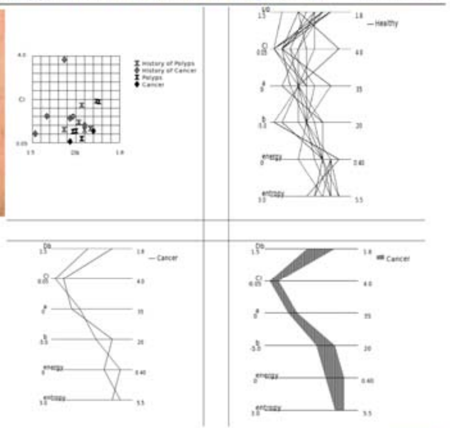


(a) Original View of the raw dataset (b) Anonymization with k=2 (c) Anonymization with k=3 (d) Anonymization with k=4

Dasgupta, A. & Kosara, R. (2011). *Privacy-preserving data visualization using parallel coordinates. Visualization and Data Analysis 2011, San Francisco, SPIE.*

Why are such approaches not used in enterprise hospital information systems?

Slide 9-31 Decision Support with Par Coords in diagnostics

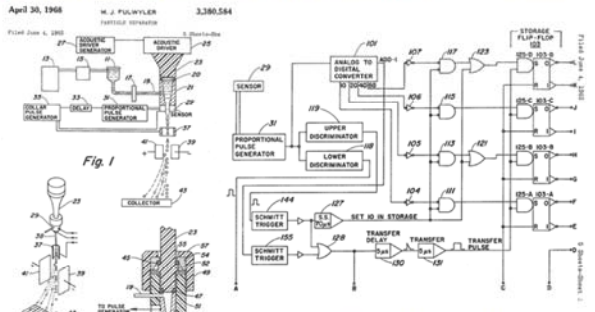


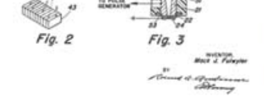
Pham, B. L. & Cai, Y. (2004) Visualization techniques for tongue analysis in traditional Chinese medicine.

Practical Example: Big data from Flow Cytometry (1)

Source: Stem Cell Insititute, Online: http://www.cellmedicine.com

Practical Example: Foundation of Flow Cytometry (2)

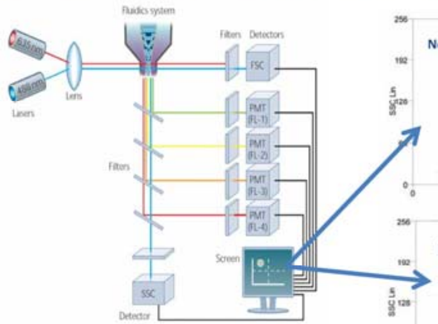


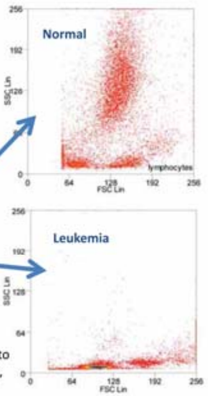


Fulwyler, M. J. (1968) US Patent 3380584 A Particle Separator, 1965 applied, 1968 published

Fulwyler, M. J. (1965) Electronic Separation of Biological Cells by Volume. *Science, 150, 3698, 910-911.*

Practical Example: Flow Cytometry (3) Immunophenotyping

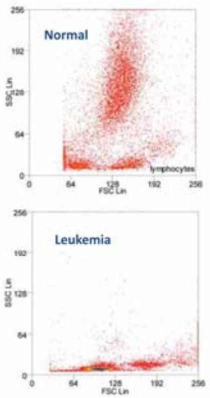




Rahman, M., Lane, A., Swindell, A. & Bartram, S. (2009) Introduction to Flow Cytometry: Principles, Data analysis, Protocols, Troubleshooting, Online available: www.abdserotec.com.

Practical Example: Flow Cytometry (4) Immunophenotyping

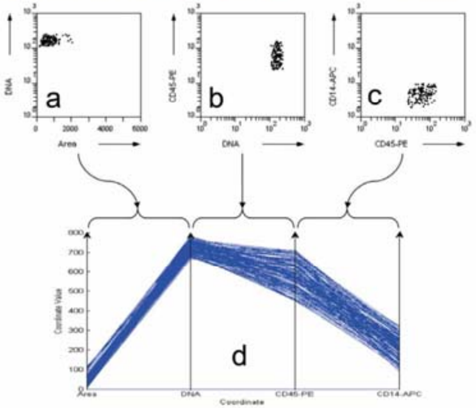
- Forward scatter channel (FSC) intensity equates to the particle's size and can also be used to distinguish between cellular debris and living cells.
- Side scatter channel (SSC) provides information about the granular content within a particle.
- Both FSC and SSC are unique for every particle, and a combination of the two may be used to differentiate different cell types in a heterogeneous sample.



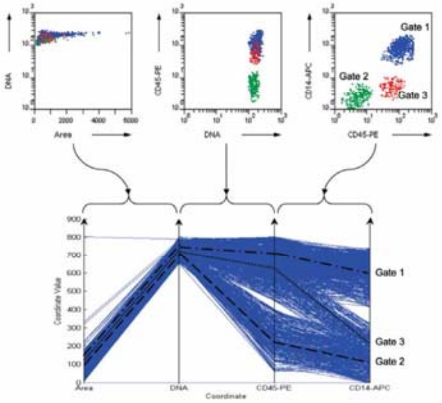
Rahman et al. (2009)

Example: 2D Parallel Coordinates in Cytometry

Streit, M., Ecker, R. C., Österreicher, K., Steiner, G. E., Bischof, H., Bangert, C., Kopp, T. & Rogojanu, R. (2006) 3D parallel coordinate systems—A new data visualization method in the context of microscopy-based multicolor tissue cytometry. *Cytometry Part A, 69A, 7, 601-611.*

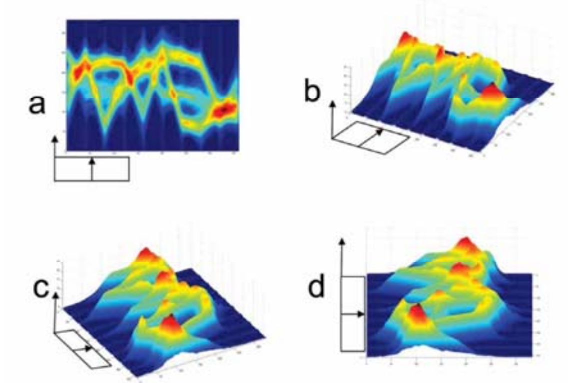


Example: Limitations of 2D Parallel Coordinates



Streit et al. (2006)

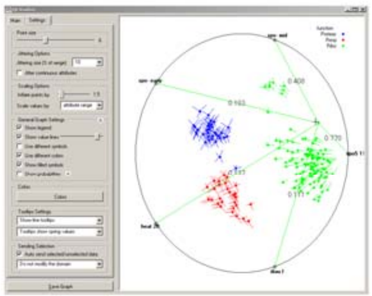
Parallel Coordinates in 3D

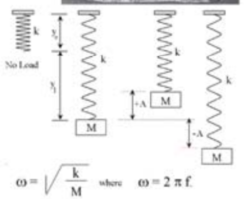


Streit et al. (2006)

Slide 9-32 RadViz – Idea based on Hooke's Law

Demšar, J., Curk, T., & Erjavec, A. Orange: Data Mining Toolbox in Python; Journal of Machine Learning Research 14:2349−2353, 2013.





Source: http://orange.biolab.si/

Slide 9-33 RadViz Principle

1) Let us consider a point $y_i = (y_1, y_2, \ldots y_n)$ from the n-dimensional space

2) This point is now mapped into a single point u in the plane of anchors: for each anchor j the stiffness of its spring is set to y_j

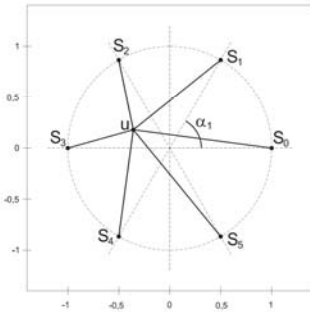
3) Now the Hooke's law is used to find the point u, where all the spring forces reach equilibrium (means they sum to 0). The position of $u = [u_1, u_2]$ is now derived by:

$$\sum_{j=1}^{n} (\vec{S_j} - \vec{u})y_i = 0 \qquad \sum_{j=1}^{n} \vec{S_j}\, y_j = \vec{u}\sum_{j=1}^{n} y_j$$

$$\vec{u} = \frac{\sum_{j=1}^{n} \vec{S_j}\, y_j}{\sum_{j=1}^{n} y_j} \qquad u_1 = \frac{\sum_{j=1}^{n} y_j \cos(\alpha_j)}{\sum_{j=1}^{n} y_j} \qquad u_2 = \frac{\sum_{j=1}^{n} y_j \sin(\alpha_j)}{\sum_{j=1}^{n} y_j}$$

Novakova, L. & Stepankova, O. (2009). *RadViz and Identification of Clusters in Multidimensional Data. 13th International Conference on Information Visualisation, 104-109.*

Slide 9-34 RadViz mapping principle and algorithm



1. Normalize the data to the interval ⟨0, 1⟩

$$\bar{x}_{ij} = \frac{x_{ij} - min_j}{max_j - min_j}$$

2. Now place the dimensional anchors

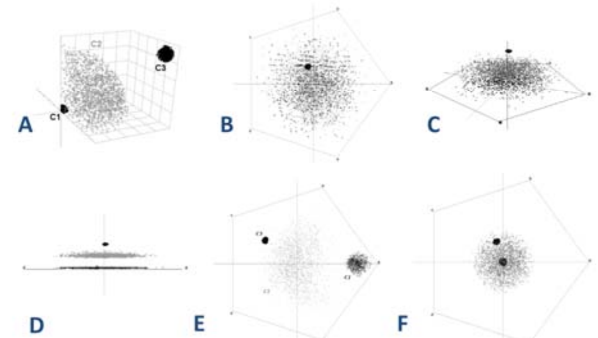
3. Now calculate the point to place each record and to draw it:

$$y_i = \sum_{j=1}^{n} \bar{x}_{ij}$$

$$\vec{u_i} = \frac{\sum_{j=1}^{n} \vec{S_j}\, \bar{x}_{ij}}{y_i}$$

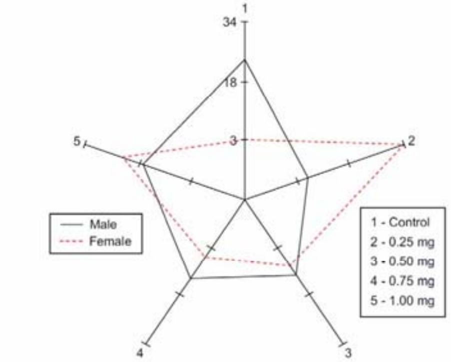
Novakova, L. & Stepankova, O. (2009). *RadViz and Identification of Clusters in Multidimensional Data. 13th International Conference on Information Visualisation, 104-109.*

Slide 9-35 RadViz for showing the existence of clusters



Novakova, L. & Stepankova, O. (2009). *RadViz and Identification of Clusters in Multidimensional Data. 13th International Conference on Information Visualisation, 104-109.*

Slide 9-36 Star plots/Radar chart/Spider-web/Polygon plot



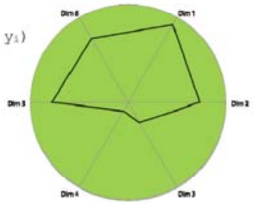
Saary, M. J. (2008) Radar plots: a useful way for presenting multivariate health care data. *Journal Of Clinical Epidemiology, 61, 4, 311-317.*

Slide 9-37 Star Plot production

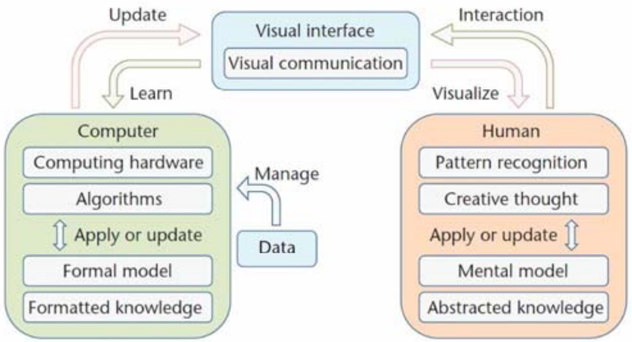
- Arrange N axes on a circle in $\mathbb{R}^2$
- $3 \leq N \leq N_{max}$
  Note: An amount of $N_{max} \leq 20$ is just useful, according to Lanzenberger et al. (2005)
- Map coordinate vectors $P \in \mathbb{R}^N$ from $\mathbb{R}^N \rightarrow \mathbb{R}^2$
- $P = \{p_1, p_2, \ldots, p_N\} \in \mathbb{R}^N$ where each p_i represents a different attribute with a different physical unit
- Each axis represents one attribute of data
- Each data record, or data point P is visualized by a line along the data points
- A Line is perceived better than points on the axes

Slide 9-38 Algorithm for drawing the axes and the lines

```
angle_sector = 2 * π / N
for each a_i from axes[]
{
angle_i = i * angle_sector
x_i = mid.x + r * cos(angle_i)
y_i = mid.y + r * sin(angle_i)
DrawLine(midpoint.x, midpoint.y, x_i, y_i)

max_i = a_i.upperBound()

scaled_val_i = a_i.value() * r / max_i
x_val_i = mid.x + scaled_val_i * cos(angle_i)

y_val_i = mid.y + scaled_val_i * sin(angle_i)
DrawLine(x_val_i, y_val_i, x_val_i-1, y_val_i-1)
}
```

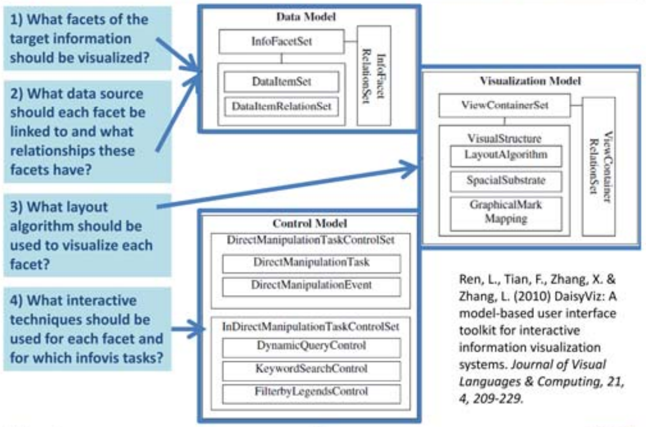


Slide 9-39 Visual Analytics is intelligent HCI



Mueller, K., Garg, S., Nam, J. E., Berg, T. & McDonnell, K. T. (2011) Can Computers Master the Art of Communication?: A Focus on Visual Analytics. *Computer Graphics and Applications, IEEE, 31, 3, 14-21.*

Slide 9-40 Design of Interactive Information Visualization



Ren, L., Tian, F., Zhang, X. & Zhang, L. (2010) DaisyViz: A model-based user interface toolkit for interactive information visualization systems. *Journal of Visual Languages & Computing, 21, 4, 209-229.*

Slide 9-41 Overview first - then zoom and filter on Demand

- 1) Overview: Gain an overview about the entire data set (know your data!);
- 2) Zoom : Zoom in on items of interest;
- 3) Filter: filter out uninteresting items – get rid of distractors – eliminate irrelevant information;
- 4) Details-on-demand: Select an item or group and provide details when needed;
- 5) Relate: View relationships among items;
- 6) History: Keep a history of actions to support undo, replay, and progressive refinement;
- 7) Extract: Allow extraction of sub-collections and of the query parameters;

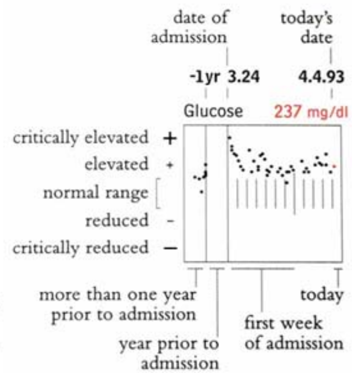
*) Shneiderman, B. (1996). *The Eyes Have It: A Task by Data Type Taxonomy for Information Visualizations. Proceedings of the 1996 IEEE Symposium on Visual Languages, 336-343.*

Slide 9-42 Letting the user interactively manipulate the data

- Focus Selection = via direct manipulation and selection tools, e.g. multi-touch (in data space a n-dim location might be indicated);
- Extent Selection = specifying extents for an interaction, e.g. via a vector of values (a range for each data dimension or a set of constraints;
- Interaction type selection = e.g. a pair of menus: one to select the space, and the other to specify the general class of the interaction;
- Interaction level selection = e.g. the magnitude of scaling that will occur at the focal point (via a slider, along with a reset button)

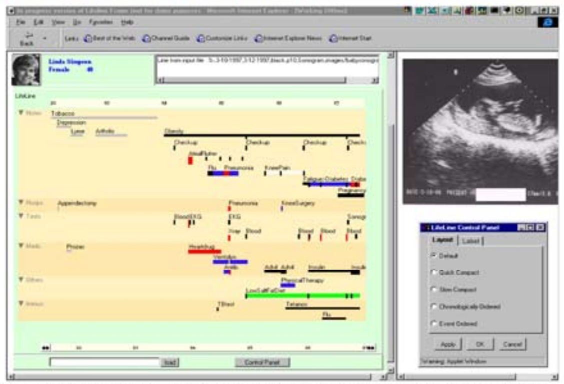
Ward, M., Grinstein, G. & Keim, D. (2010) *Interactive Data Visualization: Foundations, Techniques and Applications. Natick (MA), Peters.*

Slide 9-43 Rapid Graphical Summary of Patient Status



Powsner, S. M. & Tufte, E. R. (1994) Graphical Summary of Patient status. *The Lancet, 344, **8919**, 386-389.*

Slide 6-44 Example Project LifeLines



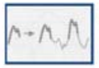
Plaisant, C., Milash, B., Rose, A., Widoff, S. & Shneiderman, B. (1996). *Life Lines: Visualizing Personal Histories. ACM CHI '96, Vancouver, BC, Canada, April 13-18, 1996.*

What are temporal analysis tasks?

Slide 6-45 Temporal analysis tasks

Classification = given a set of classes: the aim is to determine which class the dataset belongs to; a classification is often necessary as pre-processing;

Clustering = grouping data into clusters based on similarity; the similarity measure is the key aspect of the clustering process;



Search/Retrieval = look for a priori specified queries in large data sets (query-by-example), can be exact matched or approximate matched (similarity measures are needed that define the degree of exactness);

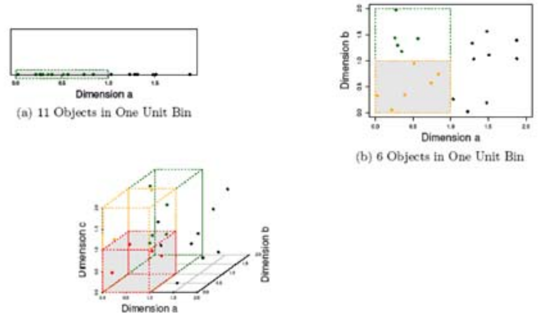
Pattern discovery = automatically discovering relevant patterns in the data, e.g. local structures in the data or combinations thereof;

Prediction = foresee likely future behaviour of data – to infer from the data collected in the past and present how the data will evolve in the future (e.g. autoregressive models, rule-based models etc.)

Aigner, W., Miksch, S., Schumann, H. & Tominski, C. (2011) *Visualization of Time-Oriented Data. Human-Computer Interaction Series. London, Springer.*

Remember: Subspace Clustering

Remember: The curse of dimensionality



(a) 11 Objects in One Unit Bin

(b) 6 Objects in One Unit Bin

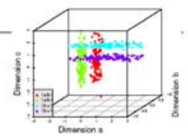
(c) 4 Objects in One Unit Bin

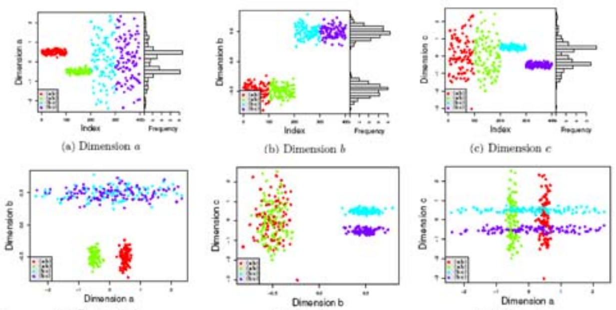
Repeat some definitions

- Dataset - consists of a matrix of data values, rows represent individual instances and columns represent dimensions.
- Instance - refers to a vector of *d* measurements.
- Cluster - group of instances in a dataset that are more similar to each other than to other instances. Often, similarity is measured using a distance metric over some or all of the dimensions in the dataset.
- Subspace - is a subset of the *d* dimensions of a given dataset.
- Subspace Clustering – seek to find clusters in a dataset by selecting the most *relevant* dimensions for each cluster separately .
- Feature Selection - process of determining and selecting the dimensions (features) that are most relevant to the data mining task.

Parsons et al. SIGKDD Explorations 2004

Parsons, L., Haque, E. & Liu, H. 2004. Subspace clustering for high dimensional data: a review. SIGKDD Explorations 6, (1), 90-105.



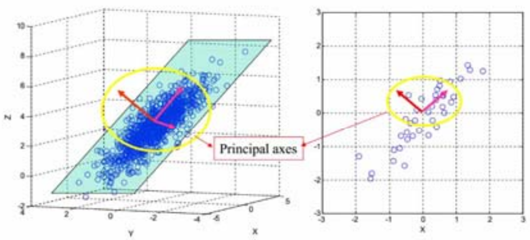


(a) Dimension *a* (b) Dimension *b* (c) Dimension *c*

(a) Dims *a* & *b* (b) Dims *b* & *c* (c) Dims *a* & *c*

Similar: Principal Component Analysis (PCA)

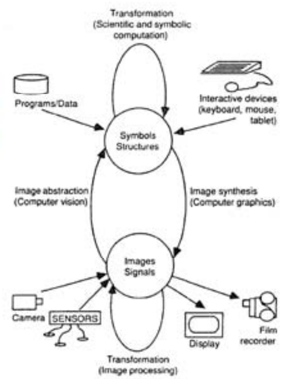
- Bellman (1957): The more dimensions, the more sparse the space becomes, and distance measures are less meaningful



05 Conclusion and Future Outlook

Slide 9-14 We can conclude that Visualization is ...

- ... the common denominator of Computational sciences
- ... the transformation of the symbolic into the geometric
- ... the support of human perception
- ... facilitating knowledge discovery in data



McCormick, B. (1987) Scientific and Engineering Research Opportunities. *Computer graphics, 21, 6.*

Slide 6-46 Future Outlook

- Time (e.g. entropy) and Space (e.g. topology)
- Knowledge Discovery from "unstructured" ;-) (Forrester: >80%) data and applications of structured components as methods to index and organize data -> Content Analytics
- Open data, Big data, sometimes: small data
- Integration in "real-world" (e.g. Hospital), mobile
- How can we measure the benefits of visual analysis as compared to traditional methods?
- Can (and how can) we develop powerful visual analytics tools **for the non-expert end user**?

Thank you!

Questions

Sample Questions (1)

- What is semiotic engineering?
- Please explain the process of intelligent interactive information visualization!
- What is the difference between visualization and visual analytics?
- Explain the model of perceptual visual processing according to Ware (2004)!
- What was the historical start of systematic visual analytics? Why is this an important example?
- Please describe very shortly 6 of the most important visualization techniques!
- Transform five given data points into parallel coordinates!
- How can you ensure data protection in using parallel coordinates?
- What is the basic idea of RadViz?
- For which problem would you use a star-plot visualization?

Sample Questions (2)

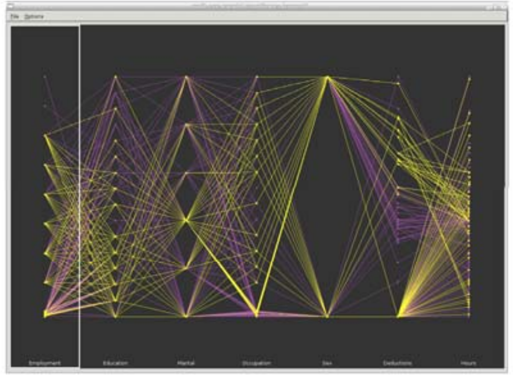
- What are the basic design principles of interactive intelligent visualization?
- What is the visual information seeking mantra of Shneiderman (1996)?
- Which concepts are important to let the end user interactively manipulate the data?
- What is the problem involved in looking at neonatal polysomnographic recordings?
- Why is time very important in medical informatics?
- What was the goal of LifeLines by Plaisant et al (1996)?
- Which temporal analysis tasks can you determine?
- Why is pattern discovery in medical informatics so important?
- What is the aim of foreseeing the future behaviour of medical data?

Appendix

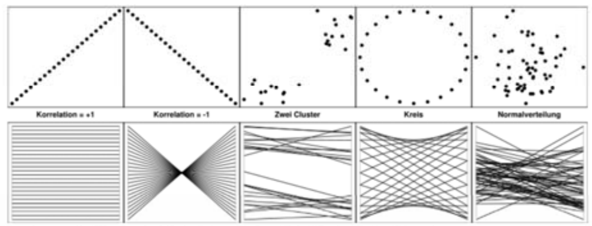
Some useful links

- http://vis.lbl.gov/Events/SC07/Drosophila/ (some really cool examples of high-dimensional data)
- http://people.cs.uchicago.edu/~wiseman/chernoff (Chernoff Faces in Java)
- http://lib.stat.emu.edu (Iris sample data set)
- http://graphics.stanford.edu/data/voldata (113-slice MRI data set of CT studies of cadaver heads)

Appendix: Parallel Coordinates in a Vis Software in R



http://datamining.togaware.com



Zur Visualisierung von hochdimensionalen Daten in der Statistik müssen drei wichtige Aspekte beachtet werden:

die Anordnung der Achsen

Die Anordnung der Achsen ist entscheidend für die Suche nach Strukturen in den Daten. In einer typischen Datenanalyse werden meist viele Anordnungen ausprobiert. Es wurden Anordnungsheuristiken entwickelt, die Einblicke in interessante Strukturen erlauben.[7]

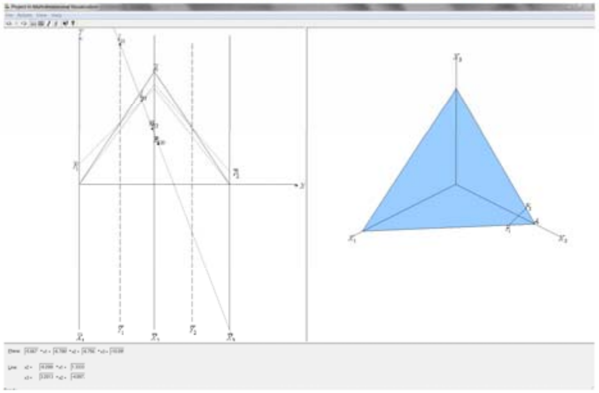
die Rotation der Achsen (Daten)

Da die i-te Koordinate durch die Ecke auf der i-ten Achse bestimmt wird, kann eine Rotation der Achsen (= Rotation der Daten) ein anderes Bild ergeben. Die beiden linken Grafiken können als Rotation der Achsen (oder Daten) um 90 Grad aufgefasst werden. Trotz gleicher Struktur ergeben sich unterschiedliche Strukturen in den parallelen Koordinaten.

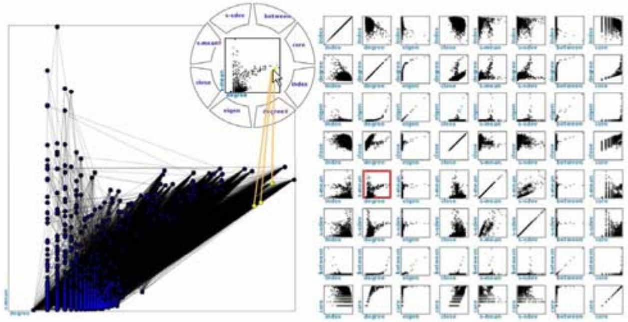
die Skalierung der Achsen

Die parallelen Koordinaten sind im Wesentlichen eine Aneinanderreihung von Linien zwischen Paaren von Koordinatenachsen.[5] Daher sollten die Variablen auf einen ähnlichen Maßstab skaliert sein. Verschiedene Skalierungen können ebenfalls interessante Einsichten in die Daten geben.

Visual Multidimensional Geometry and its Applications (1)

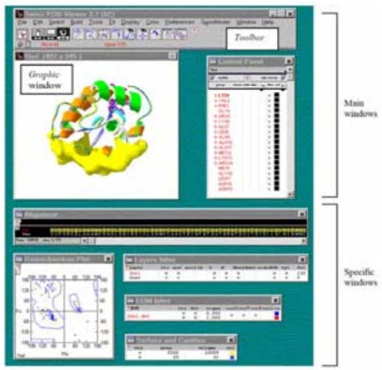


Appendix: Node-link graphs to visualize biological networks



Viau, C., McGuffin, M. J., Chiricota, Y. & Jurisica, I. (2010) The FlowVizMenu and Parallel Scatterplot Matrix: Hybrid Multidimensional Visualizations for Network Exploration. *Visualization and Computer Graphics, IEEE Transactions on, 16,* ***6, 1100-1108.***

Appendix: Deep View Working Environment - Swiss PDB



http://www.expasy.org

Appendix: Visual Analytics for Epidemiologists

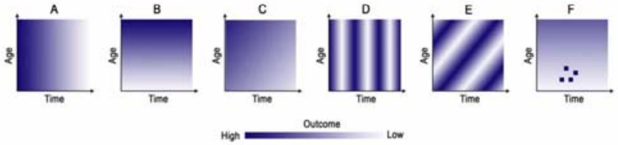
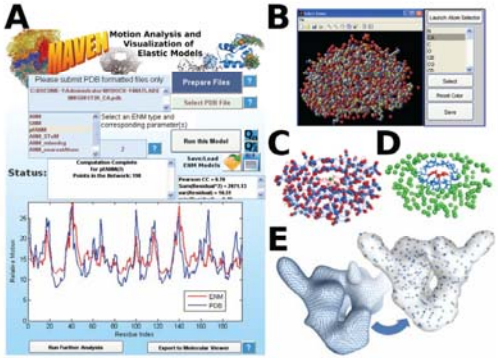


Figure 1. Typical patterns observed in image plots used to study the association between age, time, and the disease of interest.
doi:10.1371/journal.pone.0014683.g001

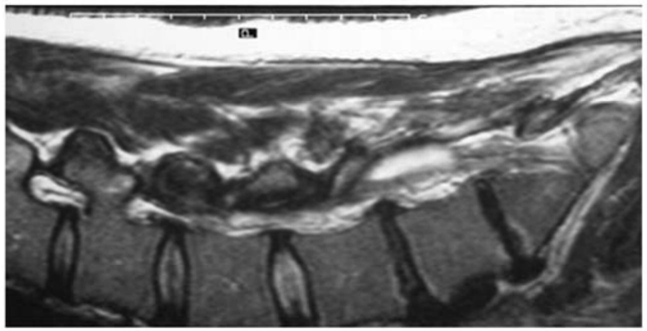
Chui, K. K. H., Wenger, J. B., Cohen, S. A. & Naumova, E. N. (2011) Visual Analytics for Epidemiologists: Understanding the Interactions Between Age, Time, and Disease with Multi-Panel Graphs. *Plos One, 6,* ***2.***

Appendix: Motion Analysis & Visualization of Elastic Models

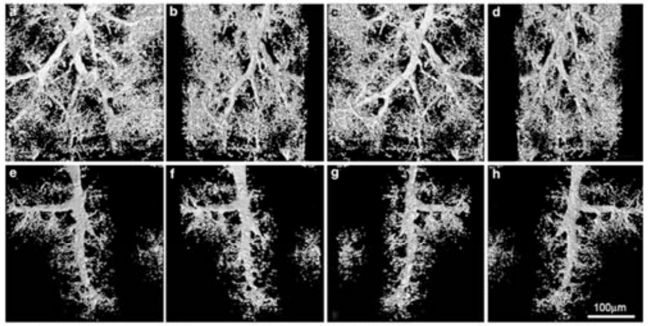
Zimmermann, M., Kloczkowski, A. & Jernigan, R. (2011) MAVENs: Motion analysis and visualization of elastic networks and structural ensembles. *Bmc Bioinformatics, 12, 1, 264.*



Typical direct image

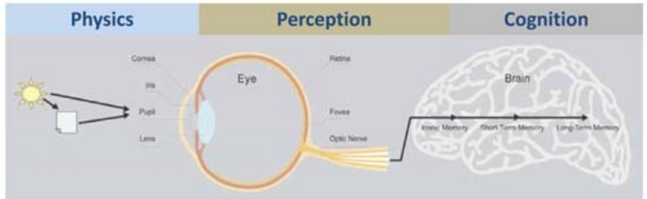


Erginousakis, D. et al. 2011. Comparative Prospective Randomized Study Comparing Conservative Treatment and Percutaneous Disk Decompression for Treatment of Intervertebral Disk Herniation. *Radiology, 260, (2), 487-493.*



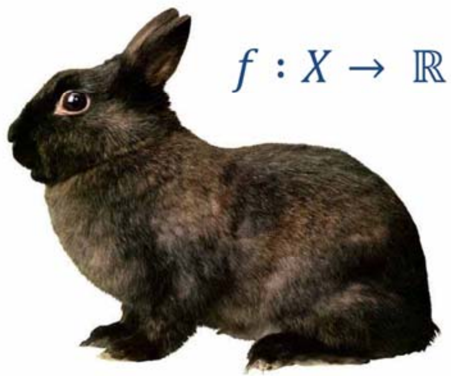
Dutly, A. E., Kugathasan, L., Trogadis, J. E., Keshavjee, S. H., Stewart, D. J. & Courtman, D. W. 2006. Fluorescent microangiography (FMA): an improved tool to visualize the pulmonary microvasculature. *Lab Invest, 86, (4), 409-416.*

Repetition: From Physics of Light to Cognition of Thought



Few, S. (2006) *Information Dashboard Design. Sebastopol (CA), O'Reilly.*

Remember



$$f : X \rightarrow \mathbb{R}$$

Remember: Data – Information (it is a visualization task!)

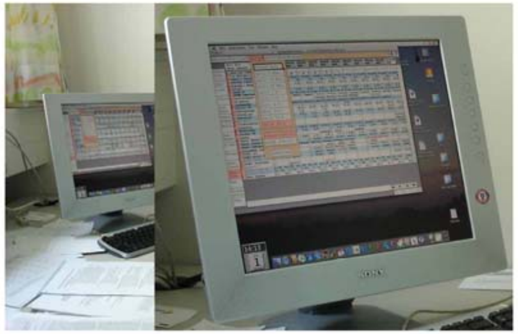
Each multivariate observation can be seen as a data point in an *n*-dimensional vector space

$\mathbf{x}_i = [x_{i1}, \dots, x_{in}]$

- "Look at your data"
- transfer data into information
- By use of human intelligence …
- to transfer information into knowledge ($\mathbb{C} \rightarrow \mathbb{P}$)
- Challenge: To reduce the dimensionality of the data …
- … it is an information retrieval task!

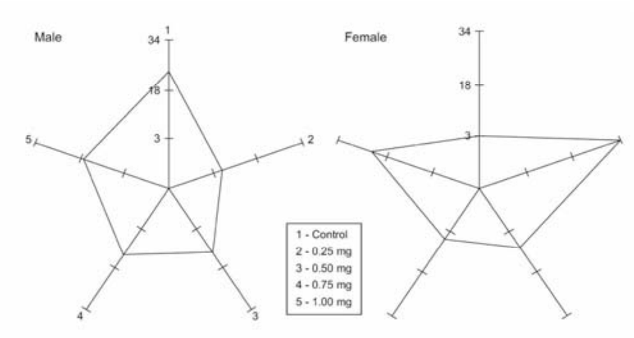
Remember: The quality can be measured by two measures:
- Recall
- Precision

Typical Problems in the Medical Clinical Domain



Holzinger, A., Hoeller, M., Bloice, M. & Urlesberger, B. (2008). *Typical Problems with developing mobile applications for health care: Some lessons learned from developing user-centered mobile applications in a hospital environment. International Conference on E-Business (ICE-B 2008), Porto (PT), IEEE, 235-240.*

Example: Star Plot Diagram - Radar Chart



Saary, M. J. (2008) Radar plots: a useful way for presenting multivariate health care data. *Journal Of Clinical Epidemiology, 61, 4, 311-317.*

The Noisy Channel

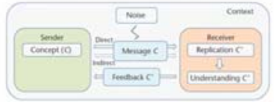
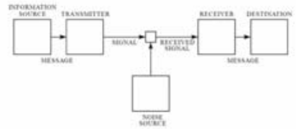


Figure 2. The interpersonal-communication protocol. A sender would like a receiver to comprehend message C, conveyed either straightforwardly or via indirect or subconscious mechanisms. However, noise in the communication channel or the receiver's failure to fully comprehend the message's intended meaning can undermine the sender's objective. An iterative clarification process eventually leads to a mutual understanding of the message.



Shannon, C. E. (1948) A Mathematical Theory of Communication. *Bell System Technical Journal, 27, 379-423.*

Slide 9-45 Example Algorithms for Selection

```
Scatterplot-Select (xDim, yDim, xMin, xMax, yMin, yMax
1 s ←0⊳ Initialize the set of records
2 for each record i ⊳ For each record,
3   do x ← NORMALIZE(i,xDim) ⊳ derive the location,
4      y ← NORMALIZE(i,yDim)
5      if xMin < x < xMax and yMin < x < yMax
6         do s ← s ∪ I ⊳ select points within rectangle
7 return s
Point-in-Point-Polygon(xs, ys, numPoints, x,y)
1 j ← numPoints -1
2 oddNodes ← false
3 for i←0 to numPoints -1
4   do if ys[i]<y and ys[j]>=y or ys[j]<y and ys[i]>=y
5      do if xs[i]+(y-ys[i]/(ys[j]-ys[i])*(xs[j]-xs[i]<x
6         do oddNodes ← not oddNodes
7      j ← I
8 return oddNodes
```

Ward, M., Grinstein, G. & Keim, D. (2010) *Interactive Data Visualization: Foundations, Techniques and Applications. Natick (MA), Peters.*

Slide 9-46 40 sec of neonatal Polysomnographic recording

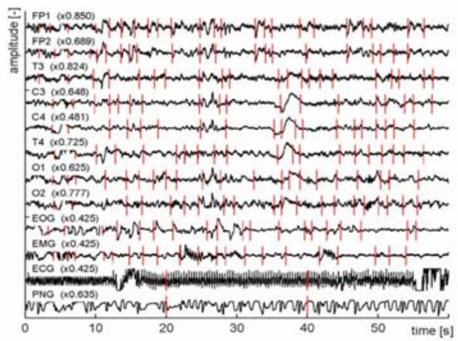
EEG signal from 8 ref. derivations: FP1, FP2, T3, T4, C3, C4, 01, 02

EOG = Electrooculogram

EMG = Electromyogram

PNG = Pneumogram

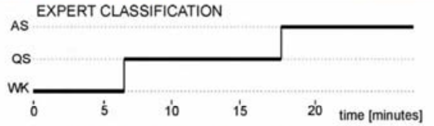
ECG = Electrocardiogram



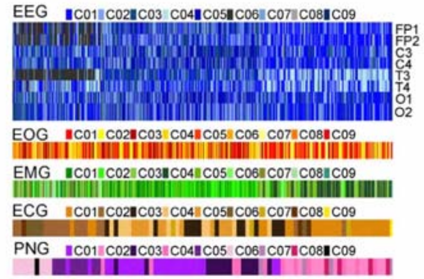
Gerla, V., Djordjevic, V., Lhotska, L. & Krajca, V. (2009). *Visualization methods used for evaluation of neonatal polysomnographic data. ITAB 2009, Information Technology and Applications in Biomedicine, Cyprus, IEEE, 1-4.*

Visual comparison of clustering results

Expert classification :
AS - active sleep,
QS - quiet sleep,
WK - wakefulness)

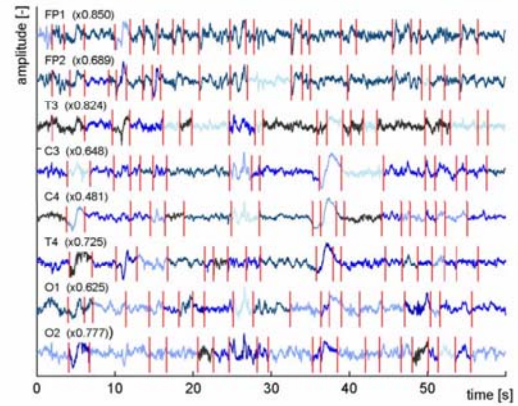


Representation of final clusters : clustering into 9 groups, displayed channels: EEG , EOG, EMG, ECG and PNG



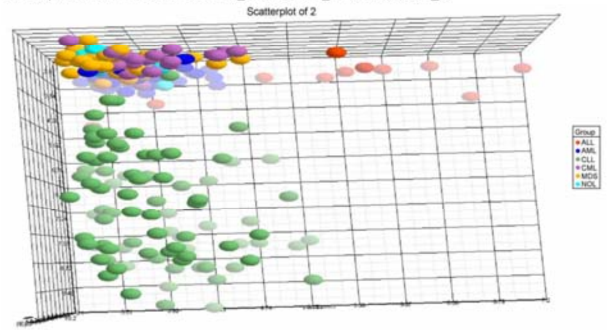
Gerla et al. (2009)

Using a unique colour for each cluster segment



8-27 Computational leukemia cancer detection 5/6

Classification CLL—ALL. Representation of the probes of the decision tree which classify the CLL and ALL to 1555158_at, 1553279_at and 1552334_at



Corchado et al. (2009)

Slide 8-28 Computational leukemia cancer detection 6/6

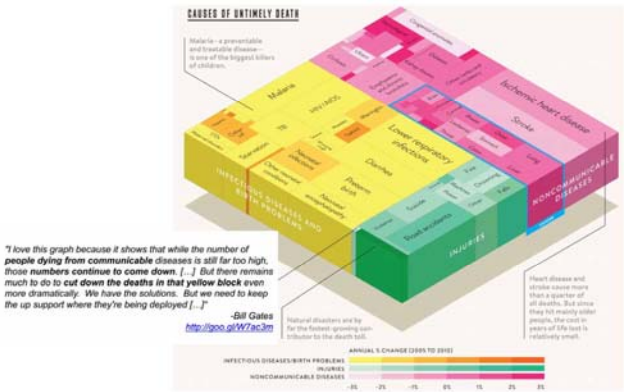
- The model of Corchado et al. (2009) combines:
- 1) methods to **reduce the dimensionality** of the original data set;
- 2) pre-processing and data filtering techniques;
- 3) a clustering method to classify patients; and
- 4) extraction of knowledge techniques
- The system reflects how human experts work in a lab, but
- 1) **reduces the time** for making predictions;
- 2) **reduces the rate of human error;** and
- 3) **works with high-dimensional data** from exon arrays

Get a feeling for big data on the internet

- Have a look at
- http://onesecond.designly.com
- And then get a feeling on our limits of cognition:

Simons, D. J. & Chabris, C. F. 1999. Gorillas in our midst: sustained inattentional blindness for dynamic events. Perception, 28, (9), 1059-1074.

https://www.youtube.com/watch?v=IGQmdoK_ZfY



No Joke: Usability of Artificial Intelligence

Home Computer of 2004

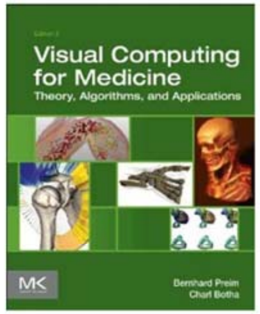
As predicted by the RAND Corporation in 1954: *

"With teletype interface and the FORTRAN language, it will be easy to use."

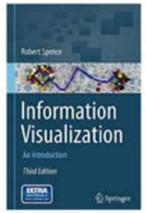
* Actually, this claim is a hoax. But BASIC on the IBM PC in 1981 was almost as hard to learn as FORTRAN in 1954, and modern languages such as Java are even harder.

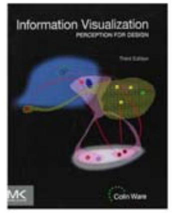
Additional Reading

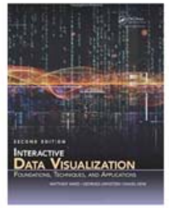
Book Recommendation



Preim, B. & Botha, C. P. 2013. Visual Computing for Medicine: Theory, Algorithms, and Applications, Morgan Kaufmann







Parallel Coordinates