3. Multidimensional Information Visualization I

Concepts for visualizing univariate to hypervariate data

Dr. Thorsten Büring, 8. November 2007, Vorlesung Wintersemester 2007/08

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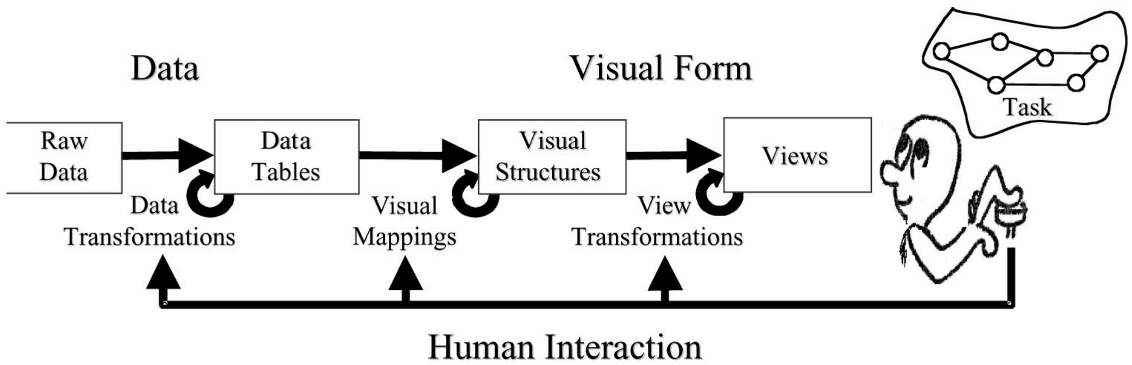
Outline

- Reference model and data terminology
- Visualizing data with < 4 variables
- Visualizing multivariable data
  - Geometric transformation
  - Glyphs
  - Pixel-based
  - Dimensional Stacking
  - Downscaling of dimensions
- Case studies: support for exploring multidimensional data
  - Rank-by-feature
  - Value & relation display
  - Dust & magnet
- Clutter reduction techniques

Topics of next lecture: Multidimensional Information Visualization II

Information Visualization

- The use of computer-supported, interactive, visual representations of abstract data to amplify cognition (Card et al. 1999)
- How to construct interactive visual representations?
- Reference Model for Visualization



Raw Data: idiosyncratic formats
Data Tables: relations (cases by variables) + meta-data
Visual Structures: spatial substrates + marks + graphical properties
Views: graphical parameters (position, scaling, clipping, …)

Card et al. 1999

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Data Table

- Cases (observations)
- Variables (aka attributes)
- Example car data set
  - 406 cases
  - 8 variables for each case
- Metadata
  - Descriptive information about the data
  - Units, e.g. lbs., mph, inches
  - Constraints, e.g. if var1is '41', then var7 can only be '11' or '3'
  - Data types

	$Variable_x$	$Variable_y$	...
$Case_i$	$Value_{ix}$	$Value_{iy}$	...
$Case_j$	$Value_{jx}$	$Value_{jy}$	...
$Case_k$	$Value_{kx}$	$Value_{ky}$	...
...	...	...	...

	mpg	cylinders	engine displ.	horsepower	weight	acceleration	prod. year	origin
Chevrolet C. M.	18	8	307	130	3504	12	70	USA
Datsun PL510	27	4	97	88	2130	14,5	70	Asia
Audi 100 LS	24	4	107	90	2430	14,5	70	Europe
...	...	...	...	...	...	...	...	...

Dimensionality of Data

- On how many variables was a data case measured?
- 1 variable – Univariate
- 2 variables – Bivariate
- 3 variables – Trivariate
- Above 3 variables – Hypervariate aka multivariate aka multivariable data
- Visualizations that encode multivariable data are called multidimensional visualizations
- Visualizing multivariable data is one of the most challenging tasks in Information Visualization

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Data Types

- Nominal (categorical)
  - Unordered set
  - Operators: $=$, $\neq$
  - Example: car origin (Europe, USA, Asia)
- Ordinal
  - Possess a natural order
  - Operators: $<$, $>$
  - Example: ratings, school grades
- Quantitative
  - Allow for arithmetic operations
  - Operators: *, /, +, -
  - Example: acceleration in seconds
- Also subtypes exist: e.g. quantitative geographic (geographic coordinates), quantitative time

Data Transformation

- Transformation of raw data into data tables can involve loss or gain of information
  - Classing: quantitative to ordinal data by dividing values into ranges, e.g. acceleration into <slow, medium, fast>
  - Nominal to ordinal data by sorting the values lexicographically
  - Derived values e.g. calculating statistical summaries (mean, median…)
  - Derived structures (e.g. sorting cases and / or variables)
  - Sampling (determining a representative subset of the data set)
  - Aggregation of data (e.g. determining frequencies)
- Deal with errors, missing values and duplicates

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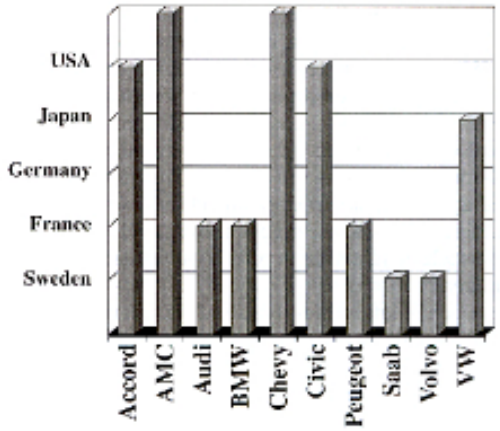
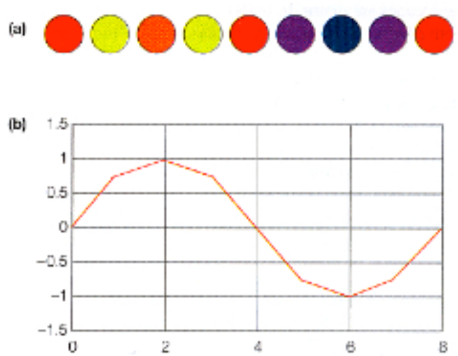
Objectives of Visual Structures

- Various mappings possible
- Quality factors of mapping
  - Expressiveness - all and only the data in the data table are represented in the structure
  - Increased effectiveness compared to another mapping
    - Faster to interpret
    - Can convey more distinctions
    - Leads to fewer errors in interpretation
    - See previous lecture on perception!



Incorrect!



Card et al. 1999

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Topics of next lecture: Multidimensional Information Visualization II

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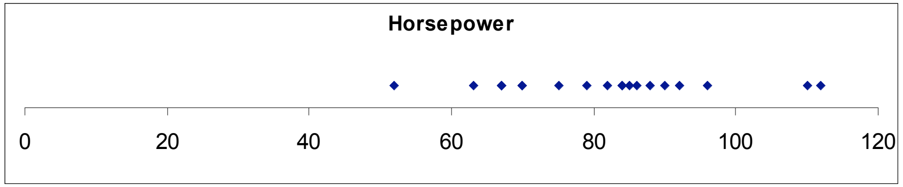
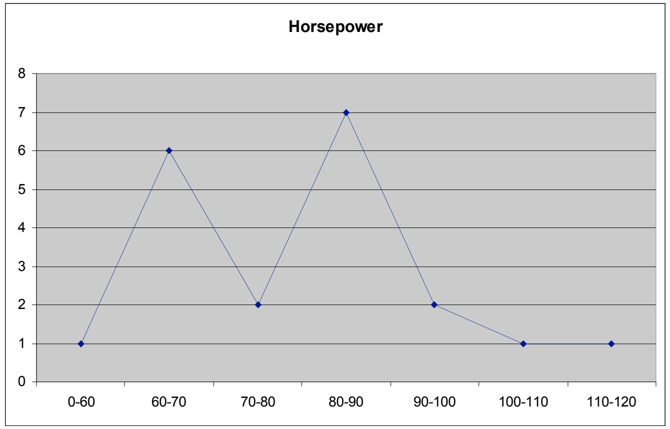
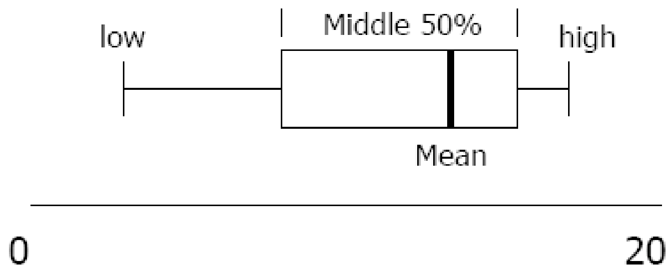
Univariate Data



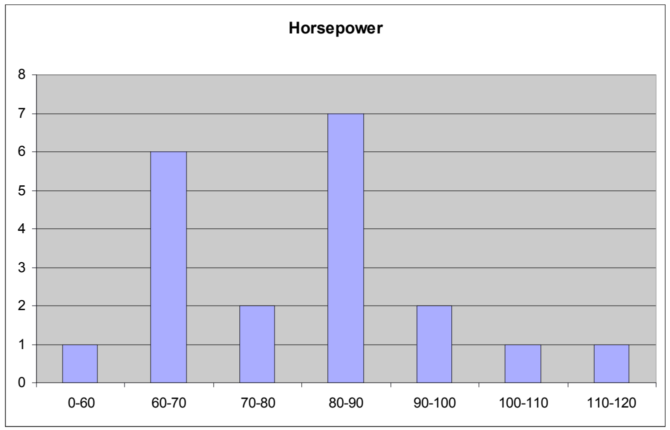
Plot



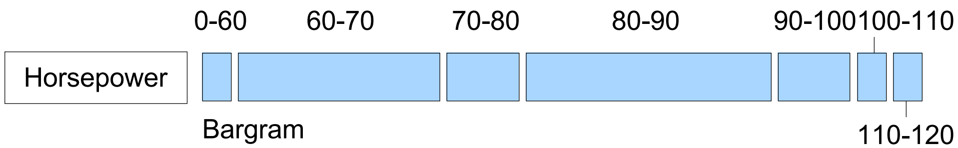
Line graph - not very reasonable in this case



Boxplot



Histogram



Bargram

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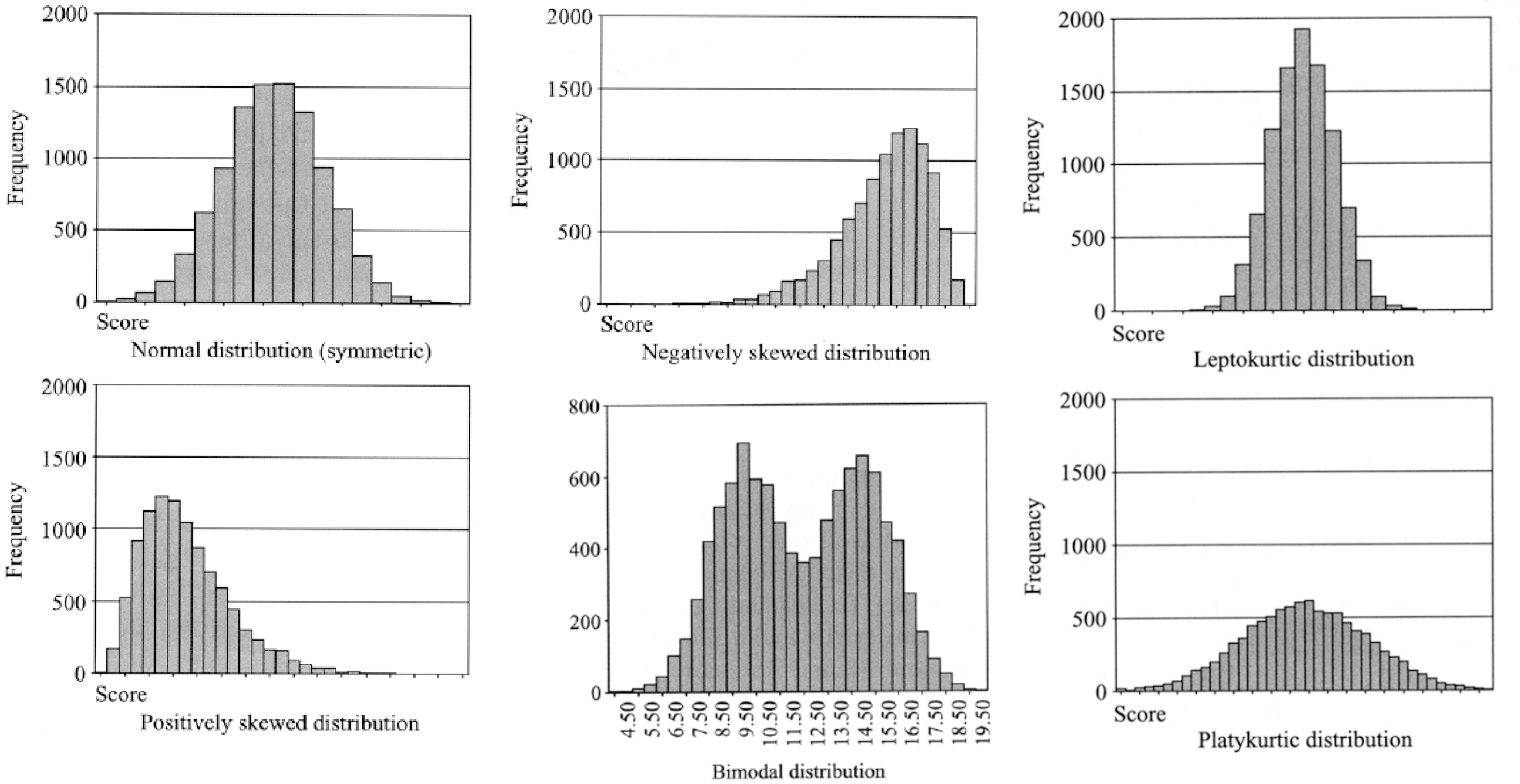
Frequency Distribution Analysis



Images from Field & Hole 2003

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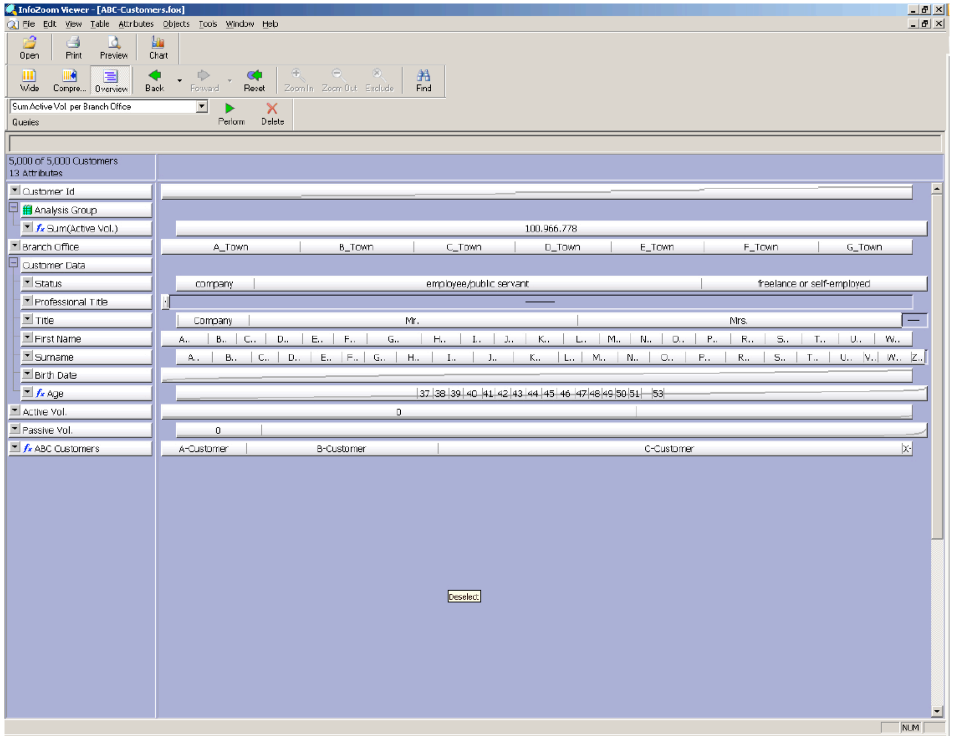
Interactive Bargrams

- InfoZoom Viewer – free download http://www.infozoom.com/deu/download/index.htm
- Demo



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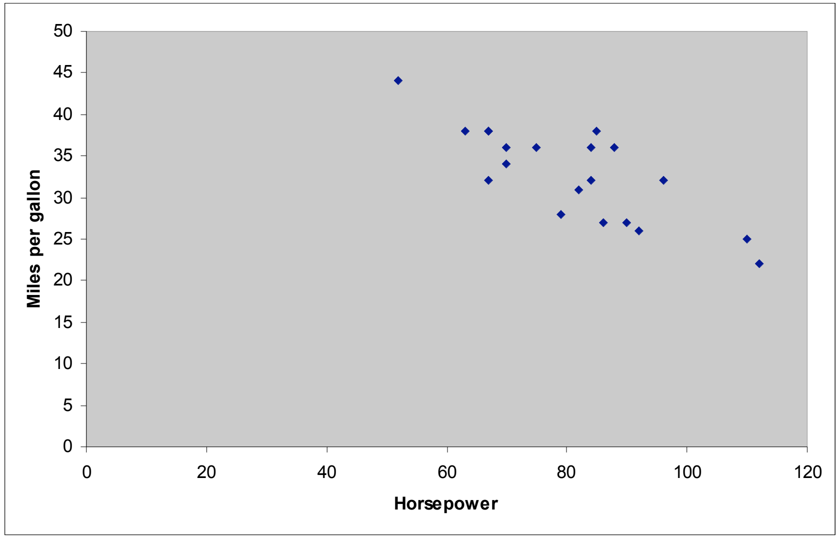
Bivariate Data

- Most common for displaying bivariate data is the scatterplot
- Each spatial dimension is assigned a (usually quantitative) axis variable
- Cases are mapped to a spatial position according to the data values for the axes
- Users can easily identify global trends, local trade-offs, outliners ...
- Potential problems?



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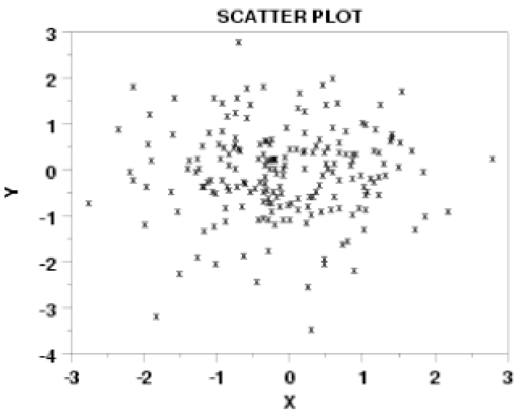
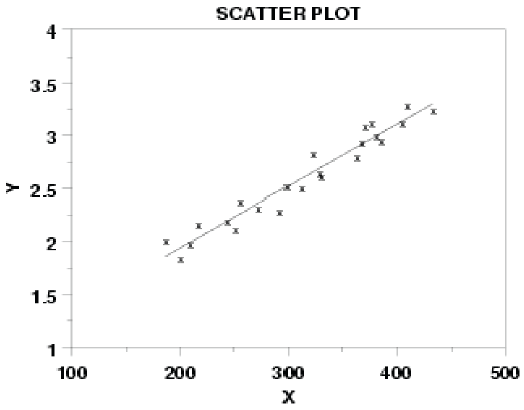
Scatterplot Analysis

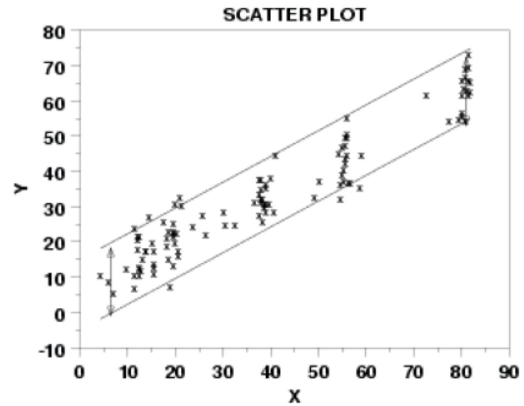
No relationship



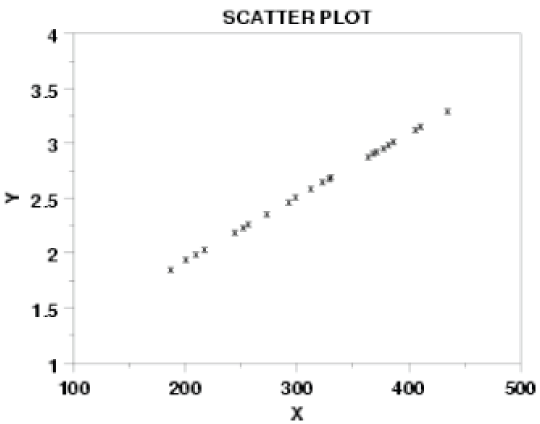
Strong linear (positive correlation)



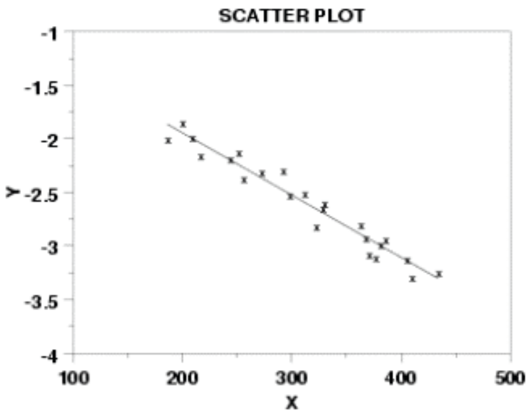
Homoscedastic



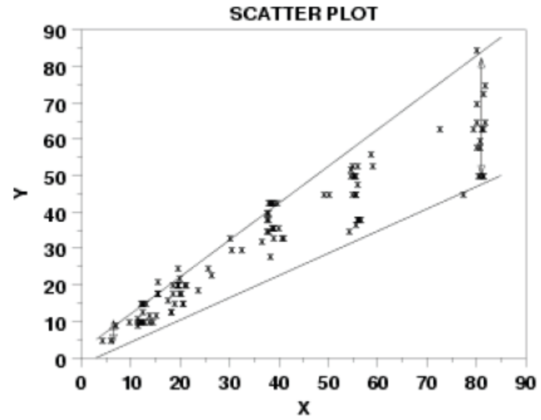
Exact linear (positive correlation)



Strong linear (negative correlation)



Heteroscedastic



http://www.itl.nist.gov/div898/handbook/eda/section3/eda33q.htm

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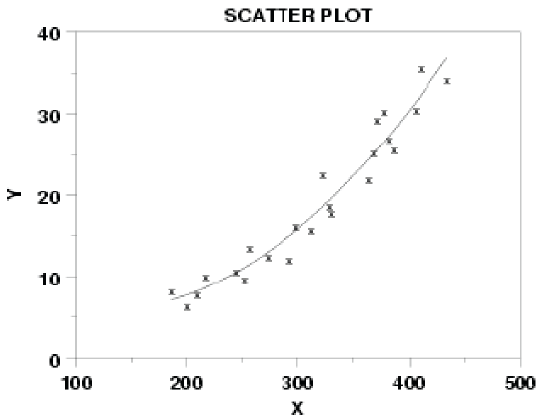
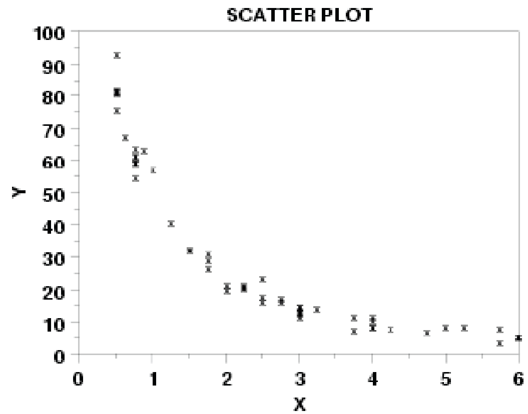
Scatterplot Analysis

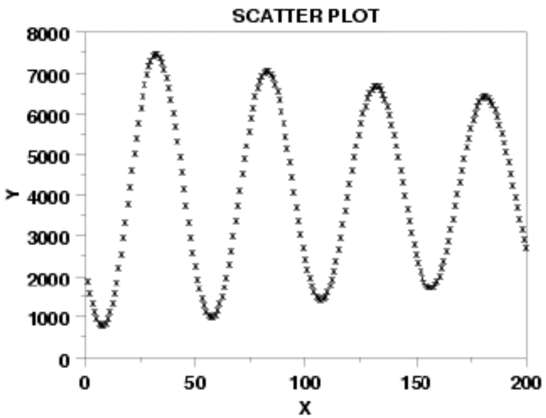
Quadratic relationship



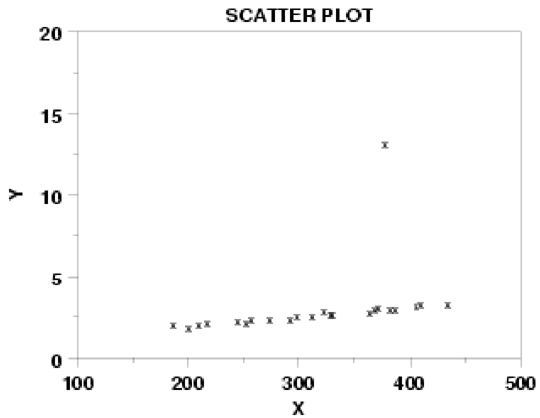
Exponential relationship



Sinusoidal relationship (damped)



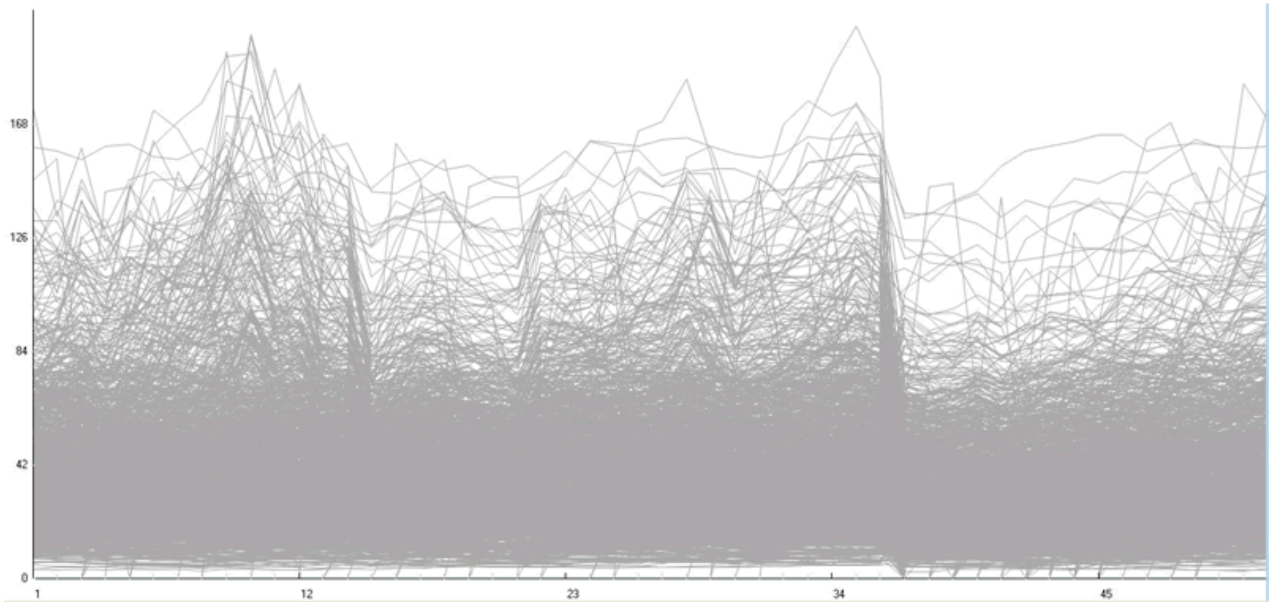
Outlier



http://www.itl.nist.gov/div898/handbook/eda/section3/eda33q.htm

Time-Based Bivariate Data

- Plot of time series
  - X-axis represents time
  - Y-axis a function of time
- Closing prices of 1,430 individual stocks across 52 weeks of time



TimeSearcher, Hochheiser & Shneiderman 2004

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Time Map

- Map showing ozone trends in Los Angeles (1982-1991)
  - X-axis: month
  - Y-axis: years and weekdays (Sunday to Saturday)
  - 4 categories of ozone concentration mapped to distinct colors
- Reveals seasonal patterns
  - Ozone levels are much higher in summer months
  - High ozone days have steadily decreased
- How could this visualization be improved?

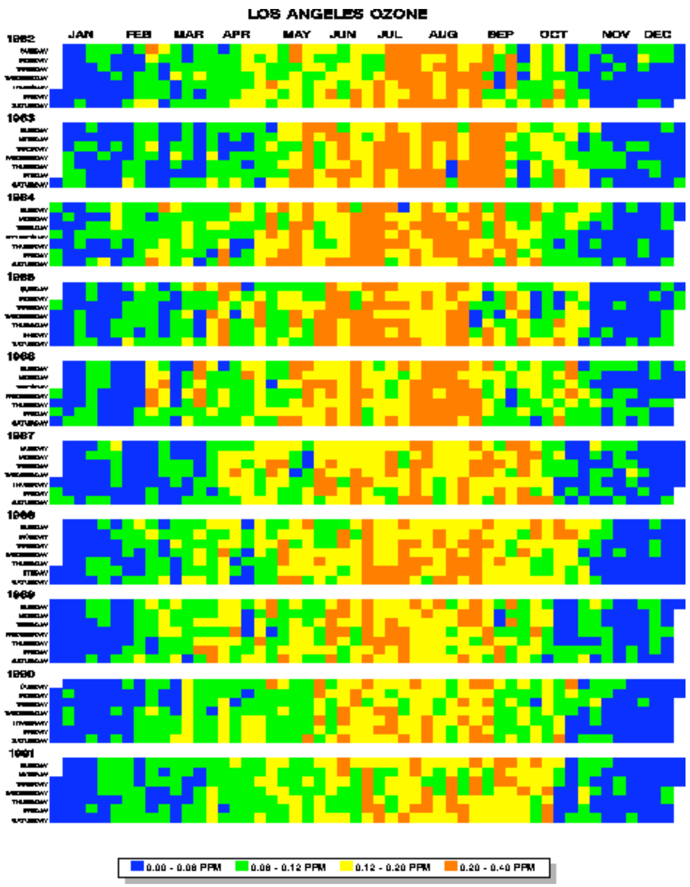

Image taken from Mintz et al. 1997

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Geographic Bivariate Data

- Size of each territory shows relative proportion of the world population living there
- Potential problem with this visualization?

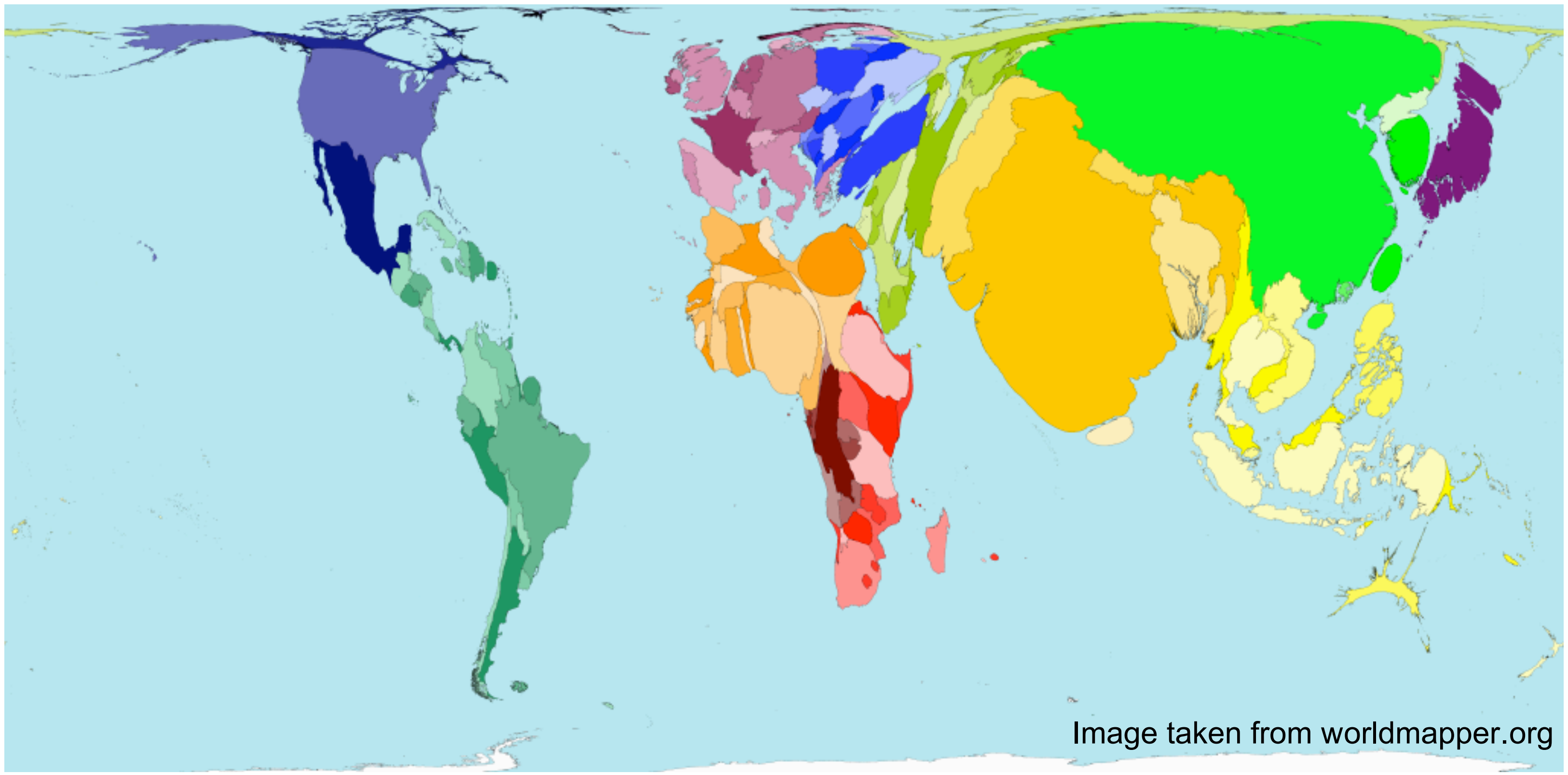

Image taken from worldmapper.org

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Distorted Map with Comparison Map

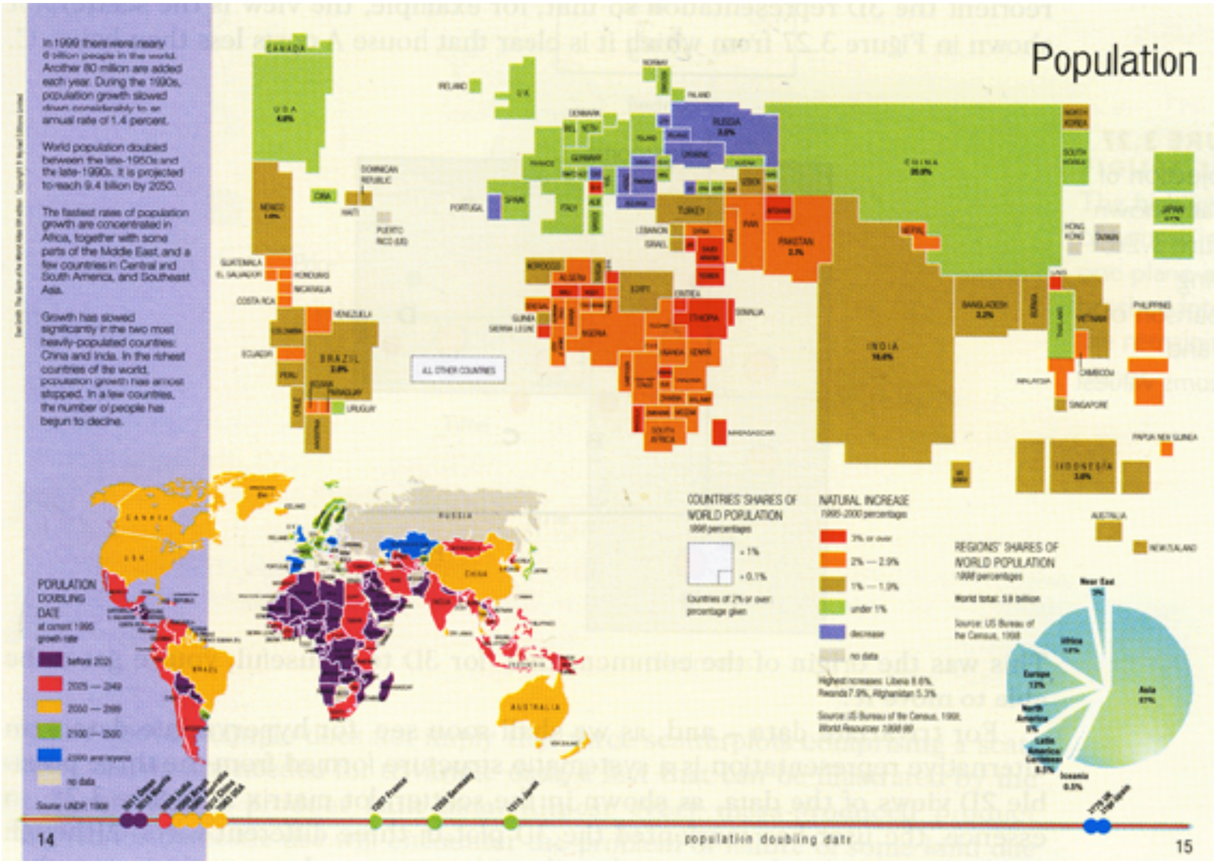

Image taken from Spence 2007

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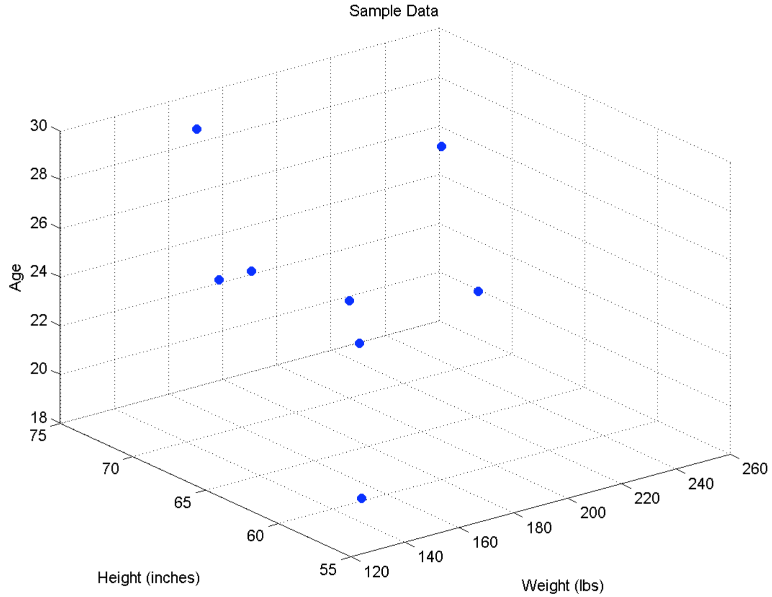
Trivariate Data

- Tempting: map each variable to each dimension of a 3D scatterplot
- Occlusion of points with different positions
- Problem with static representation?



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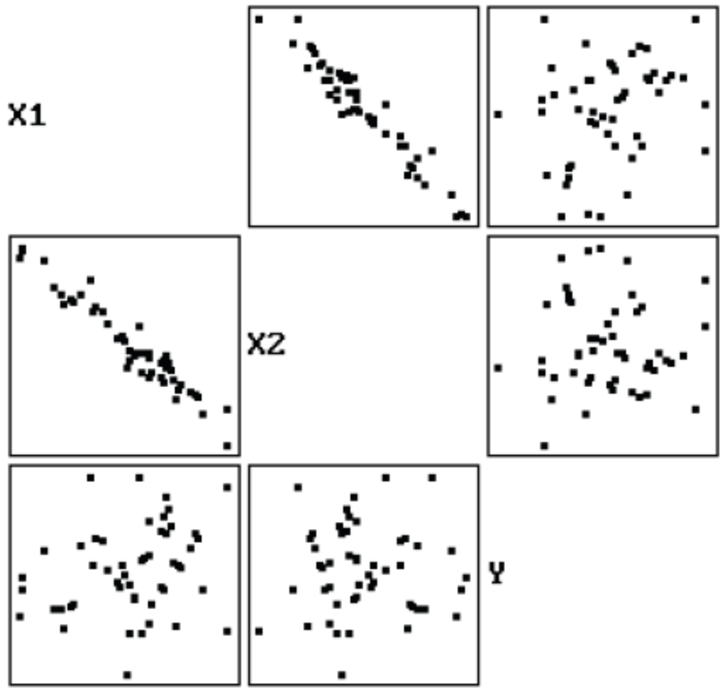
Scatterplot Matrix

- Matrix of all pairwise scatterplot views of the data
- Easy to understand by using familiar and powerful scatterplot representation
- Can serve as a good starting point for data exploration
- Increased demand for display space
- Increased cognitive load caused by redundant data



Cleveland 1993

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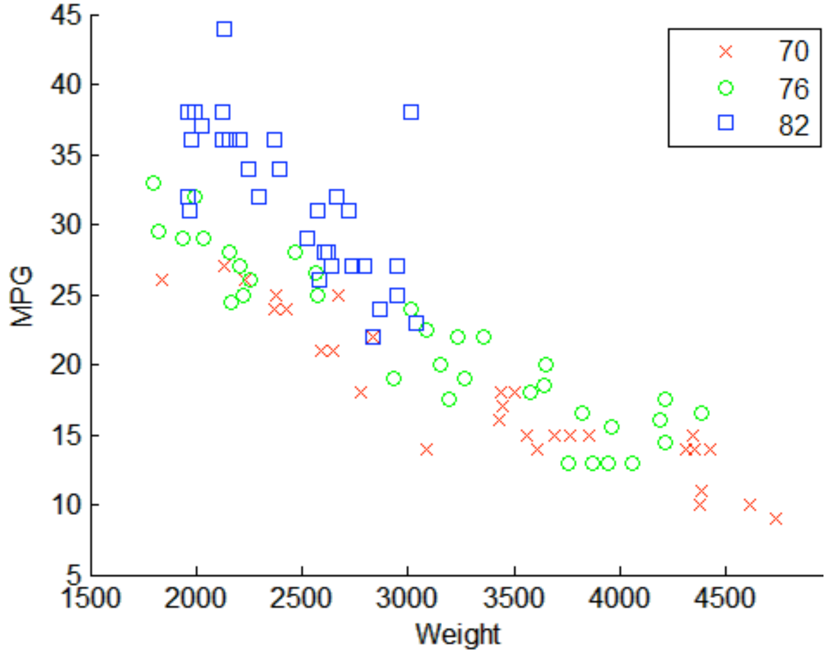
Trivariate Data

- 2D scatterplot with additional encoding
- In this case color and shape
- Shows relationship between three variables
- For color / shape coding: assumes categorical variable or classing of quantitative variable (loss of information)



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Topics of next lecture: Multidimensional Information Visualization II

Geometric Transformations

- Idea: present projections of the multidimensional data to find interesting correlations
- Most common techniques
  - Scatterplot matrix
  - Prosection matrix
  - Parallel coordinates plot

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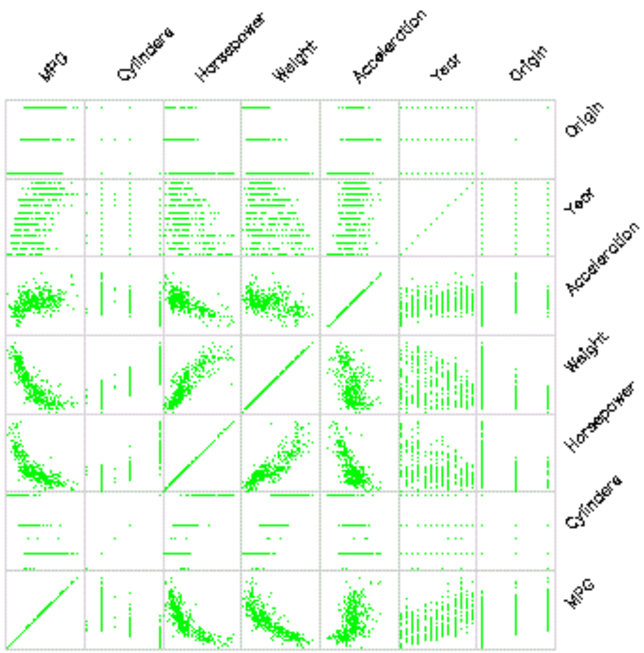
Scatterplot Matrix

- Scatterplot matrix can be scaled to > 3 variables
- Number of scatterplots increases rapidly
- n variables means n x n plots
- Diagonal maps the same variable twice
- Each pair is plotted twice, once on each side the diagonal
- Allows convenient sequential browsing of one variable compared to all other variables



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Prosection Matrix

- Scatterplot matrix with **interactive linking and brushing** (Tweedie & Spence 1996)
- **Proj**ection of a **section** of parameter space
- User select multivariable ranges, which are colored differently

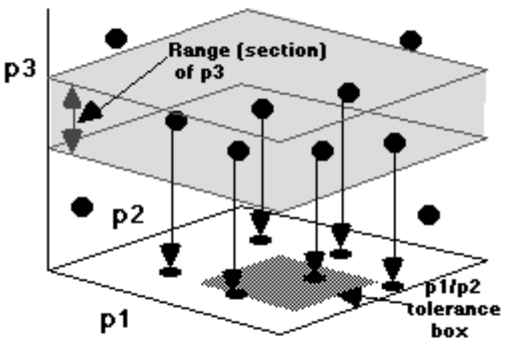

Figure 9: A section of p3 is projected onto a p1/p2 scatterplot

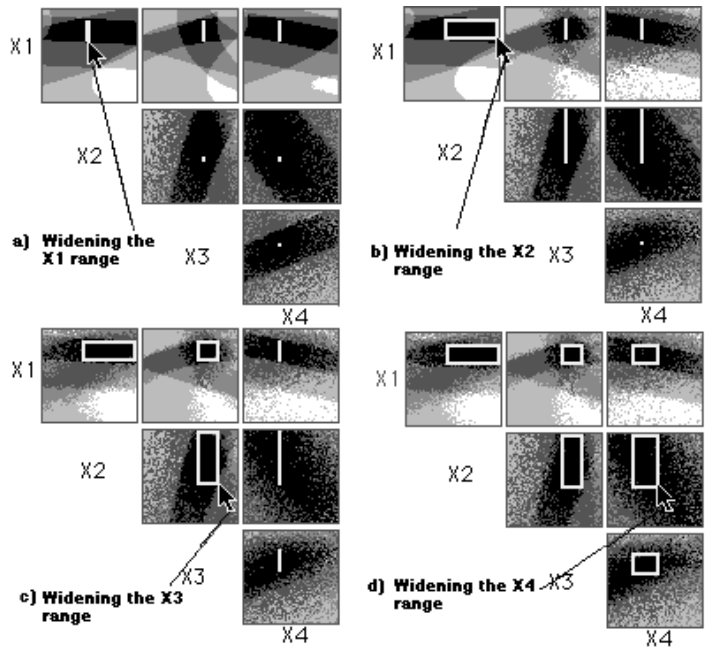

Figure 12: Gradually increasing the tolerance region so that sections of the data are projected. The boundaries become fuzzier as the ranges are adjusted.

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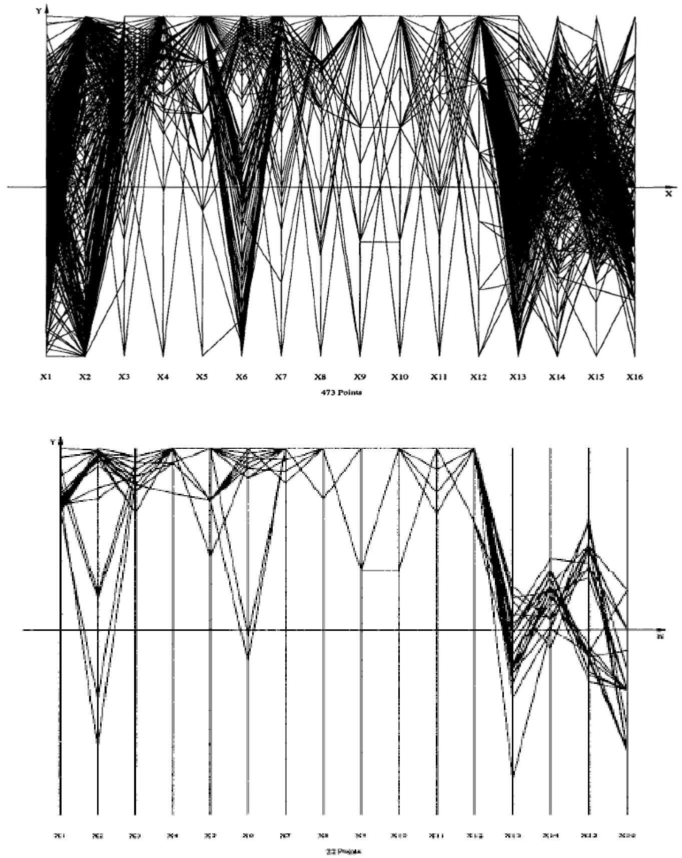
Parallel Coordinate Plot

- One vertical axis for each variable
- Every case is represented by a graph
- Graph intersects each of the vertical axis at the point corresponding to the attribute value of the case
- Popular visualization technique
- Complexity (number of axes) is directly proportional to the number of attributes (comp. scatterplot matrix)
- All attributes receive uniform treatment
- Demo
- Potential problems of this visualization?



Inselberg 1997

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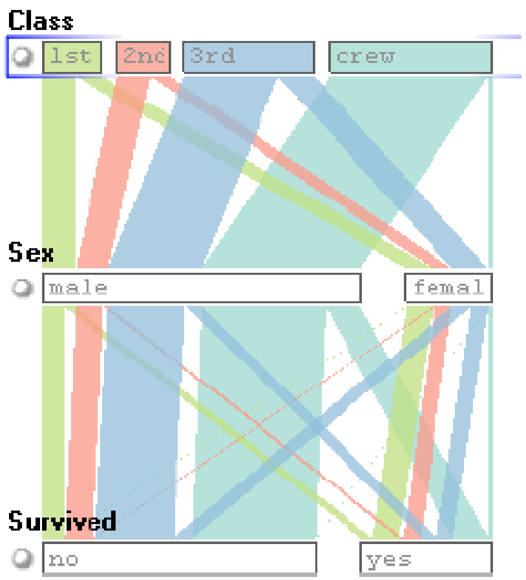
Parallel Coordinate Plot

- Bendix et al. 2005: Parallel Sets
- Parallel coordinates for categorical data
- Substitute individual data points by a frequency-based representation
- Any problems with this visualization?



	1st	2nd	3d	crew
Female (s)	141	93	90	3
Feamle (d)	4	13	106	20
Male (s)	62	25	98	670
Male (d)	118	154	422	192

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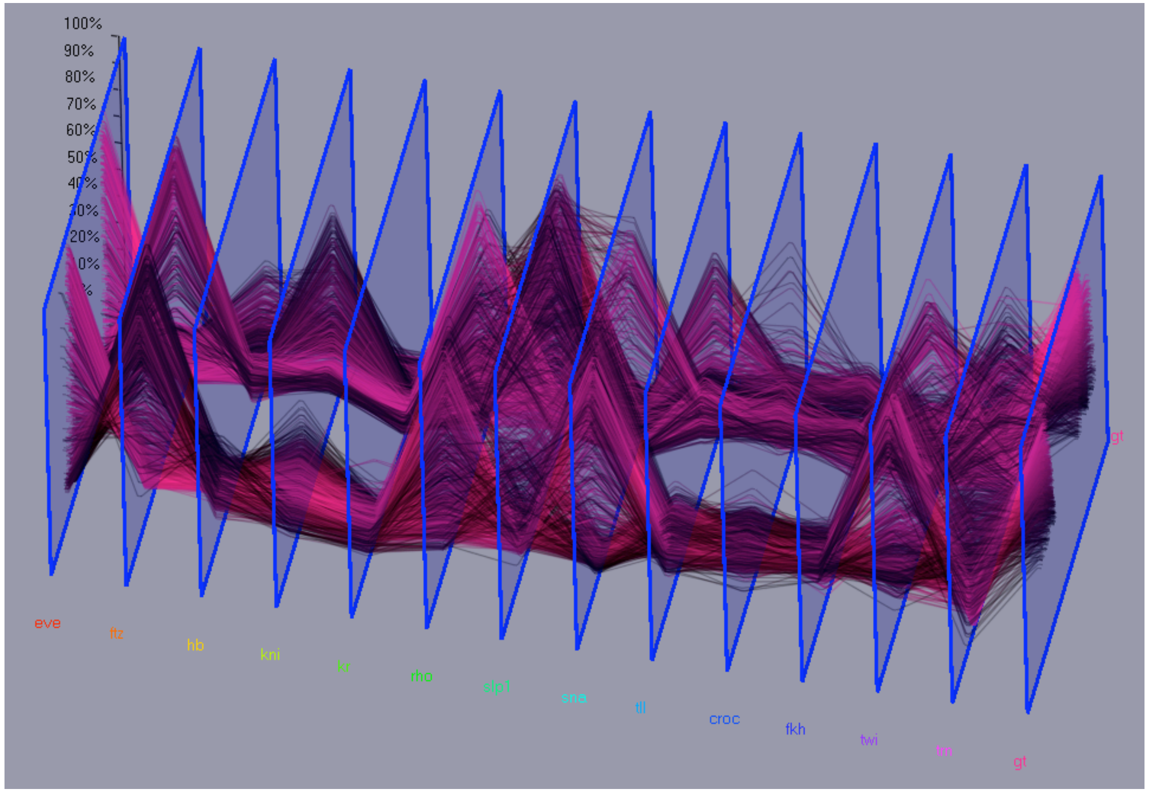
3D Parallel Coordinates

- Parallel 2D planes instead of vertical axes



http://www-vis.lbl.gov/Events/SC05/Drosophilia/index.html

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Parallel Coordinate Plot

- Try it out
  - **XmdvTool** http://davis.wpi.edu/%7Exmdv/index.html
  - **Parvis** http://home.subnet.at/flo/mv/parvis/index.html
  - **Macrofocus** http://www.macrofocus.com/public/products/infoscope.html

Geometric Transformations

- Advantages
  - Users' familiarity with scatterplots (scatterplot matrix)
  - 2D patterns can easily be identified
- Disadvantages
  - Rather limited scalability
    - Number of cases (Parallel Coordinate Plot)
    - Number of dimensions (scatterplot matrix)
  - Overplotting and overlap
  - Labeling (Parallel Coordinates)

Glyph-Based Visualizations

- Glyph-based techniques
  - Star glyph
  - Chernoff faces
  - Stick-figure
  - Shape coding
  - Color icons
- Glyph: small-sized visual symbol
  - Variables are encoded as properties of glyph
  - Each case is represented by a single glyph

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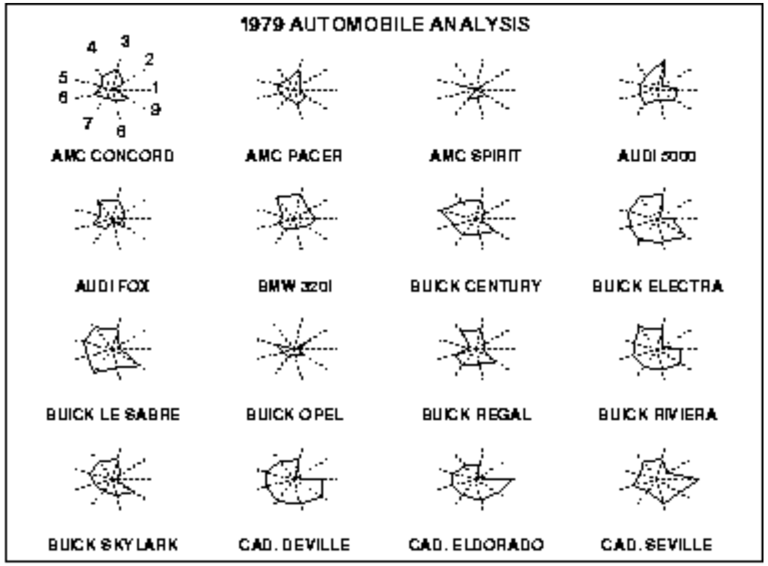
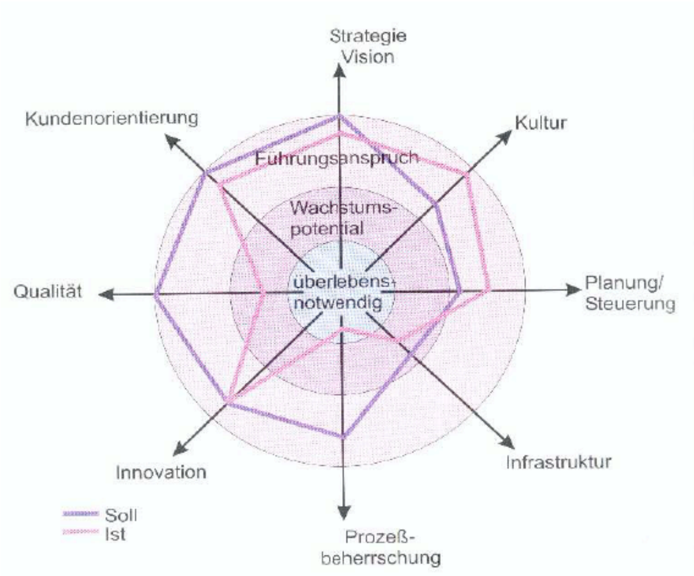
Star glyphs

- Coekin 1996
- Radial axes with equal angles
- Each axis represents a variable
- Each spoke encodes a variable's value
- May also be overlaid for better comparison

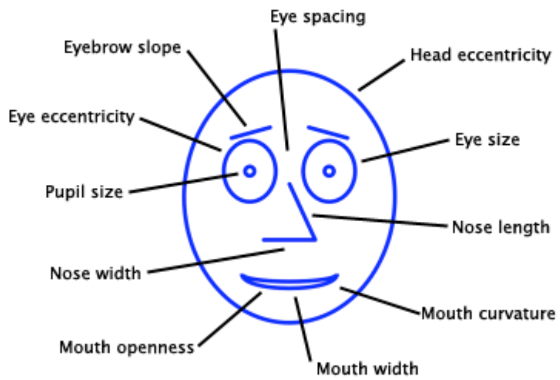


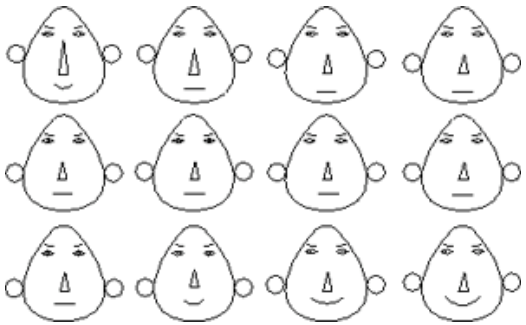
http://www.itl.nist.gov/div898/handbook/eda/section3/starplot.htm

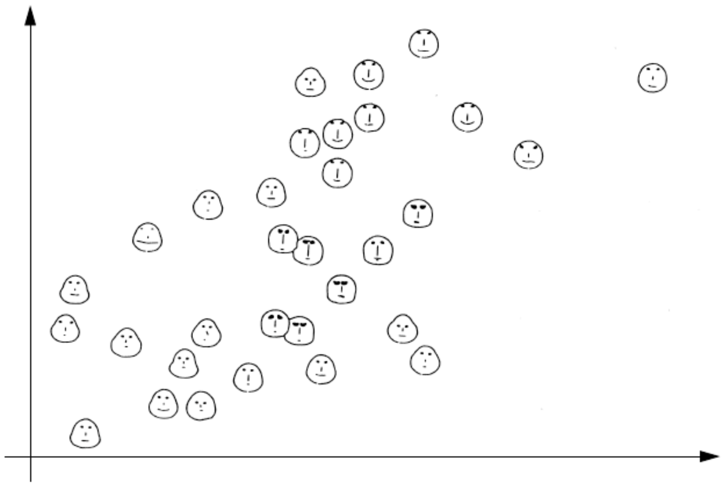


Chernoff Faces

- Chernoff 1973
- Humans are sensitive to a wide range of facial characteristics (e.g. eye size, length of a nose, etc.)
- 18 characteristics to encode data by stylized faces
- Positive evaluation results (Spence & Parr 1991)
- Some facial features seem to be able to carry more information than others (Morris et al. 1999; De Soete 1986)







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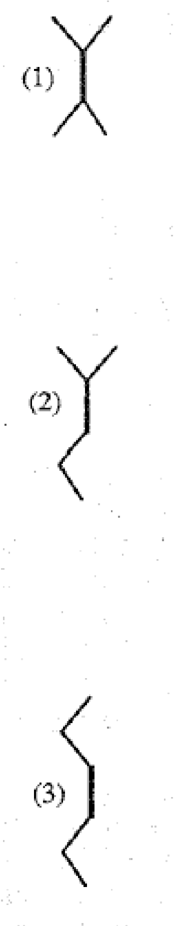
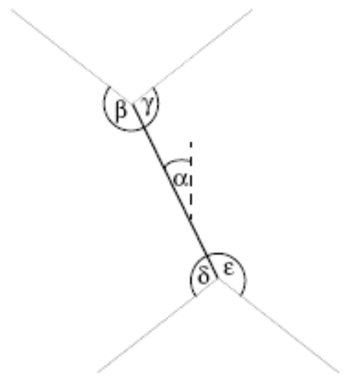
Stick-Figure Icons

- Pickett & Grinstein 1998
- Each case is represented by a stick figure
- Two attributes are mapped to XY position of the glyph
- Remaining dimensions are mapped to the angle and / or length of the 4 limbs
- When icons are densely packed a texture appears
- Texture pattern reveals characteristics of the data space
- Different members of stick-figure family for conveying different types of data structures





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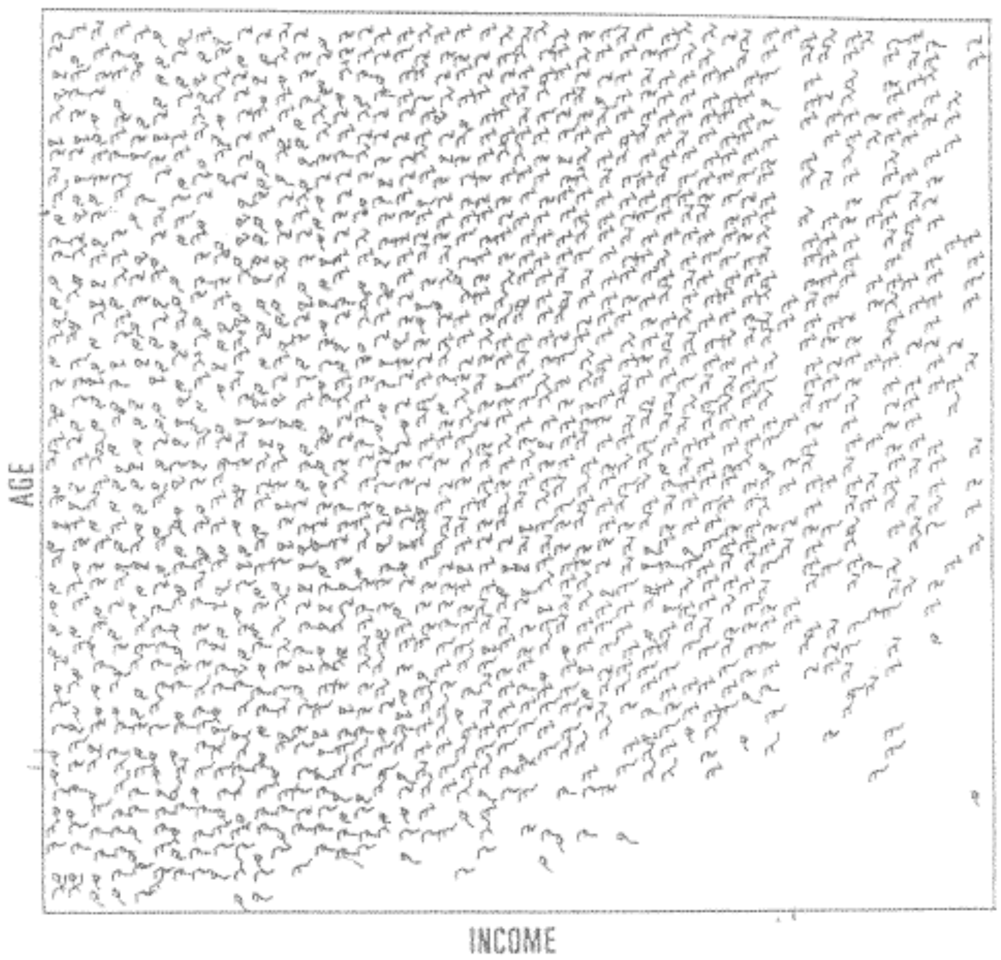
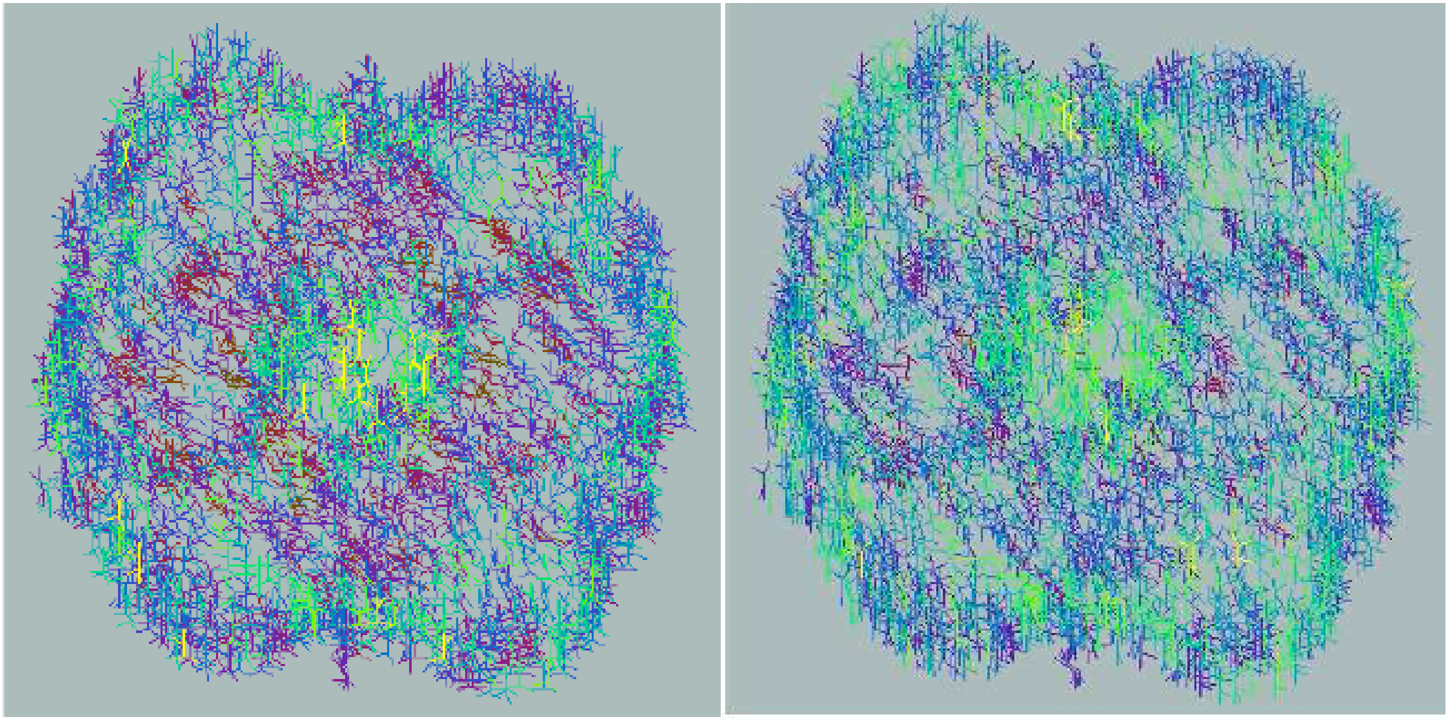
Stick-Figure Icons

- Stick-figure example
- Census data showing age (y), income (x), education, salary, language, marital status etc.
- Gender is encoded by two stick-figure families



Grinstein et al. 1989

3D Stick-Figures

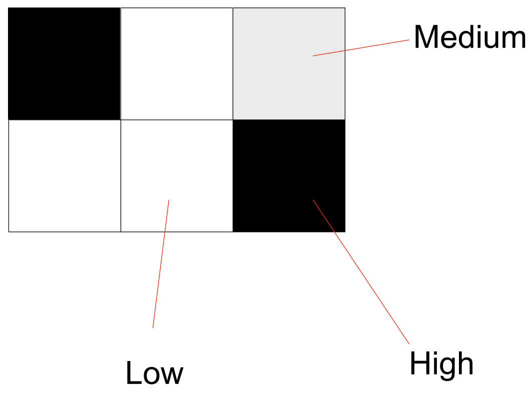


Keim 2000

Shape Coding

- Beddow 1990
- Each case is drawn as a glyph containing a rectangular grid
- Each grid cell represents one attribute
- Attribute value is encoded with gray scales
- Glyphs are positioned in a line, columns or encoded dimensions
- Highly compressed visualization without clutter and overlap (compare to stick-figures)
- Identification of promising patterns

Glyph encoding 6 attributes



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Shape Coding

- Attribute values encoded by white, grey, black
- 13 Variables gained from magnetoshere and solar wind data
- Includes one time variabel (hour/day), which has been mapped to x/y

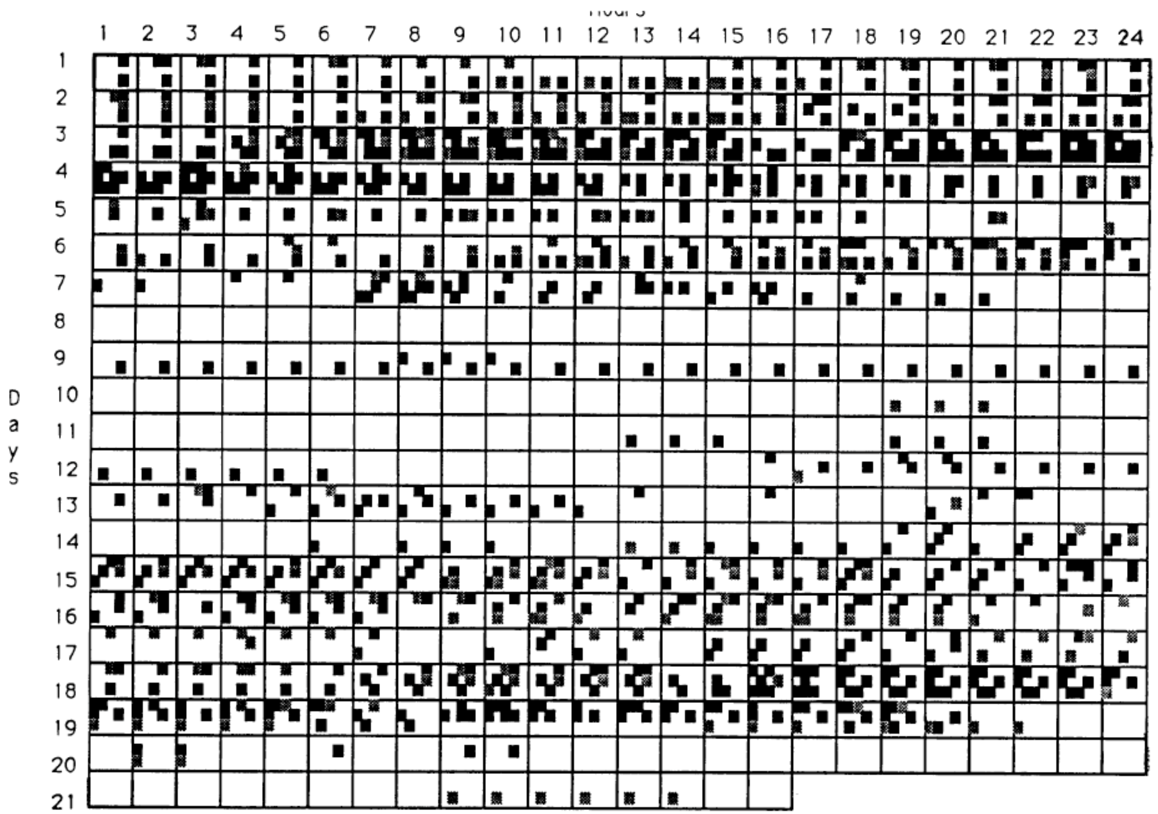
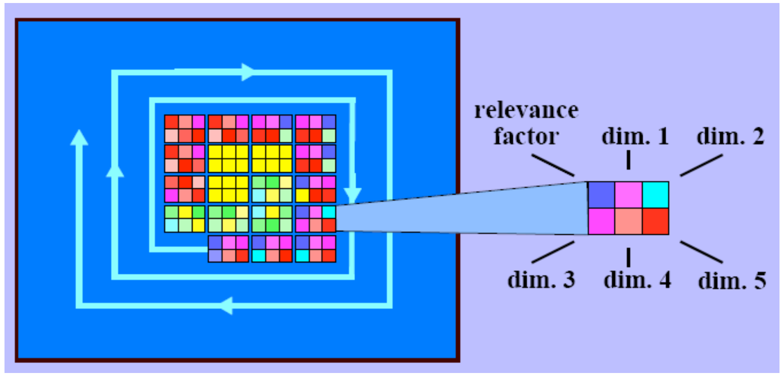


Figure 1 :
Day by Hour: Thirteen Parameters of Magnetosphere and Solar Wind Data

Color icons

- Levkowitz 1991, Keim & Kriegel 1994
- Shape coding with a focus on colors
- Arrangement is query-dependent (e.g. spiral: most relevant glyph is centered)
- What about compressing the visualization even more by using 1-pixel representations?
- Problem: users need at least 2x2 pixel per data value + pixels for borders to distinguish between the elements of the visualization
- This is different to pixel-based techniques, which will be discussed in the next lecture



Keim & Kriegel 1994

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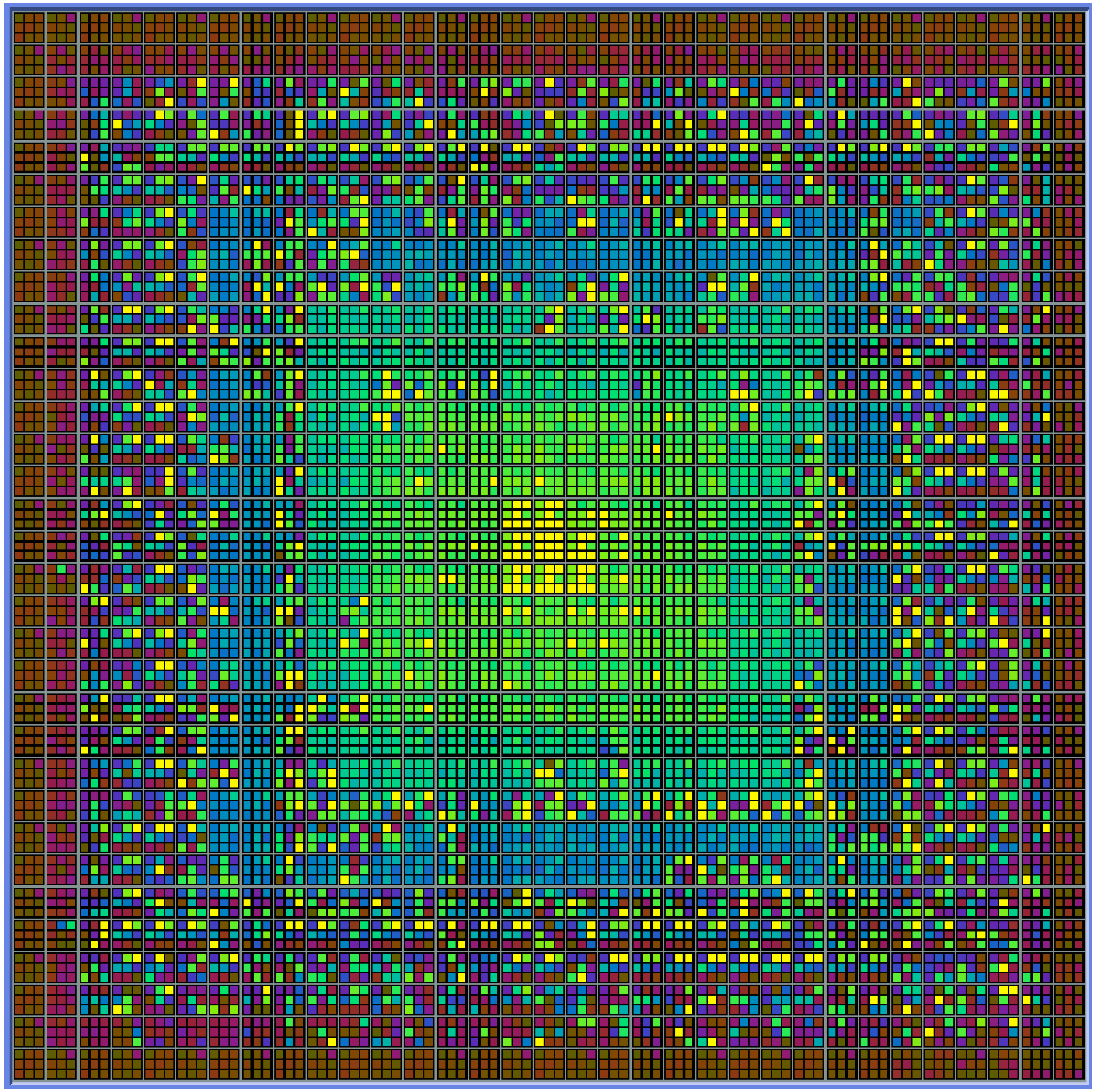

Keim 1994

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Glyph-Based Visualizations

- Advantages
  - Provide holistic overview of the information space
  - Exploit the human powerful ability of perceiving (texture) patterns and human face characteristics (Chernoff)
  - Direct metaphor of Chernoff-face-like icons (e.g. houses) may prove to be intuitive for novice users
- Disadvantages
  - Glyphs must be learned
  - Only suitable for small to medium data sets
  - Stick figures give a rather broad overview and may be difficult to interpret
  - Mappings may introduce biases in interpretation (e.g. the head shape of a Chernoff-face may be easier to perceive and compare than length of nose)