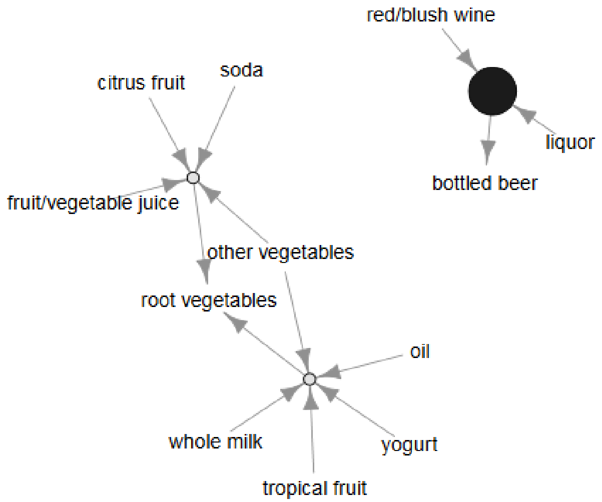
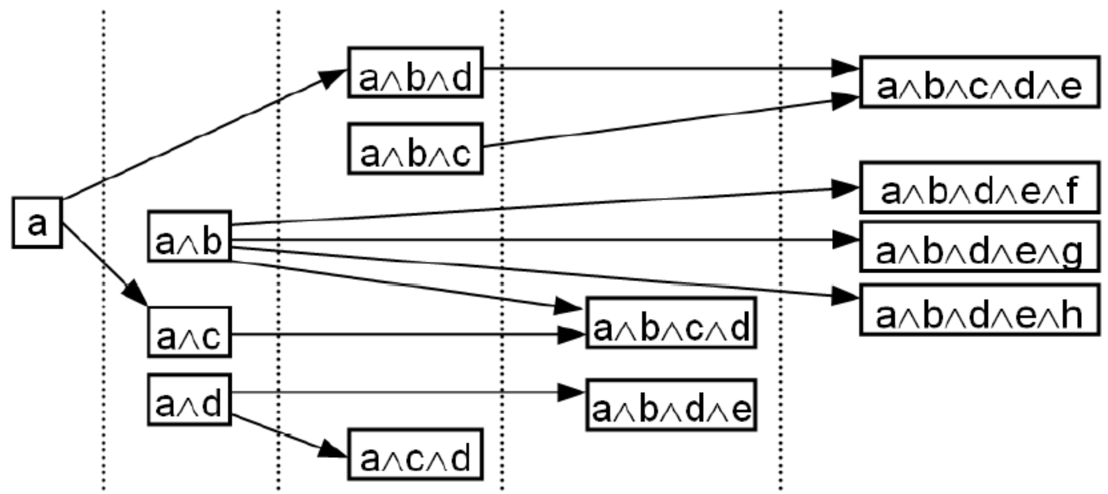
Visual Analysis of Association Rules





Outline

- Introduction
- Problem description and requirements
- Interestingness measures
- Visualization techniques
  - Graph-based techniques
  - Matrix-based techniques
- Summary & Outlook

Introduction

„Association rules

- are amongst the most important patterns that can be discovered using data mining." (Hofmann, 2000).
- Are an unsupervised learning technique leading to large result sets (Blanchard, 2006)

Essential applications:

- market basket analysis as support for cross-selling, marketing decisions and product planning.
- People who searched for i_1 and i_2 also searched for i_3
- People who bought i_1 and i_2 also bought for i_3
- Credit assessment:
  If (job=Yes) and (AnnualIncome > 50.000 €) → Credit=good
- But also medicine:
  - People with $symptom_1$ also have $symptom_2$
  - People using $drug_1$ also use $drug_2$

  Such information is relevant for efficient patient-doctor communication (diagnosis) and treatment decisions.

Introduction

- Association rules are also essential in *text mining*, where unstructured data (documents, e-Mails, presentations, scientific papers) is analyzed w.r.t. co-occurrence of words, co-authors, citations
- A corpus of documents is analyzed w.r.t. terms that occur often enough but not too often (e.g. „and“, „the“).
- A-rules reflect likely combinations of words.
- When documents are time-stamped, rules may reflect how co-occurrence of words changes.

Possible consequences of association rules:

- **Product placement**: Based on a rule $(A \Rightarrow B)$ place A and B together in a shop or catalog or website (reinforcing the effect, like a self-fulfilling prophecy).
- **Workflow analysis**: Which steps are often performed in the same sequence, e.g. in production or a surgical operation (use instrument X, use instrument Y)?

Such analysis may help to anticipate the next steps and to perform workflow support.

Association rules ($A \Rightarrow B$), are characterized by some values (both in the [0,1] interval):

- **Support**: popularity of the rule (how often A occurs),
- **Confidence**: conditional probability that a transaction that contains A also contains B. Confidence represents the reliability/precision of the rule.

Conf ($A \Rightarrow B$) = *supp* ($A \cup B$)/supp(B)

Rules with very low support are not interesting even if confidence is high. If such a (highly specific) rule is used for prediction, it often fails, since it is *overfitted* to the (training) data.

The number of association rules grows exponentially with the number of items.

Analysts are interested in rules with

- a *minimum support* (therefore *frequent item mining*) and
- *Minimum confidence* leading to threshold-based filtering.

Association rules involve a number of „hidden"

relations, e.g. $(A \Rightarrow B)$ *and* $(A \cup \{i_{new}\} \Rightarrow B)$ are related.

Analysts question: How does the incorporation or removal of an item (on LHS or RHS) influence confidence and support?

Introduction

- Algorithms to extract association rules are known as *frequent item search* (also employed for biclustering).
- The number of rules may be as high 2^n-n-1 for n items
- Pioneering work was done by RAKESH AGRAWAL (Agrawal, 1993 and the more efficient „ apriori" algorithm presented in Agrawal, 1994).
- Compared to (subspace) clustering, association rules are well-defined. Algorithms differ in strategy and performance but usually not in their results.
- Thus, we focus on visualization and interaction to get insight and knowledge from a set of association rules.

Apriori algorithm (standard approach, Agrawal, 1994):

- level wise iterative approach: After rules with itemlength *n* are searched, the algorithm explores rules with length *n+1*.

Apriori property:

- Any non-empty subset of a frequent itemset, is also a frequent item set.
- In other words: If an itemset with length *n* is not frequent, any superset of this itemset is also not frequent.

This property (similar to subspace search) is used for efficient pruning.

Application to numerical data:

Numerical data is grouped in intervals, e.g. low, middle and high income.

The thresholds for grouping should be chosen such that the support of A-rules is maximum.

Classification rules:

Association rules where the RHS is a class, e.g.
tumor_tissue = inhomogeneous & tumor_size>3 cm = yes & tumor_shape = irregular → malignant

Problem Description and Requirements

We discuss visualization and interaction techniques that employ the results of „frequent item mining“

- To provide filtering techniques for the most important rules (according to different criteria),
- to give an overview of the results,
- to present sufficient context to interpret them, e.g. contingency tables for the variables involved in a rule,
- to present details for selected subsets or single association rules and
- provide insight in the nature of association rules (correlation) and their relations, e.g. provide easy access to rules with the same LHS or RHS

Problem Description and Requirements

Scope:

- restrict to *static data*, i.e. the relation between A and B does not change over time

Furthermore, ignore

- *weighted association rules*, e.g. *people buying at least four bottles of wine, buy at least three pizza*.
- *quantitative association rules* (Srikant, 1996), e.g. „20% of married people between age of 30 and 40 have at least two cars.“ Quantitative A-rules are derived from databases with mixed numerical and categorical data.

Interestingness Measures

Interestingness measures serve to select and rank patterns based on their potential value for analysts (Sekhavat, 2012)

- Support and confidence are the classic interesting measures employed by all frameworks to support association rule mining (introduced by Agrawal, 1993)
- Other, more advanced „interestingness" measures may be involved but need experts for efficient interpretation.
- Statistical significance of a rule is assessed based on the ratio of counter examples

Interestingness Measures

Advanced measures include (Geng, 2006; Hofmann, 2000):

- *doc* (difference of confidence, [Hofmann, 2000]):

  doc(A→B):= con(A→B) - con(⌐A→ ⌐B)

  Obviously, this value may be negative

- *Added value*

  addedValue(A→B):= con(A→B) –supp (B)

- *Lift*

  lift(A→B):= con(A→B)/supp (B)

  Since supp(B) is often low, lift may reach high values, e.g. 10 or in large databases even much more. „Lift" tells you how much more (or less) likely „B" is, for a transaction with „A" compared to likelihood of B in the whole dataset.

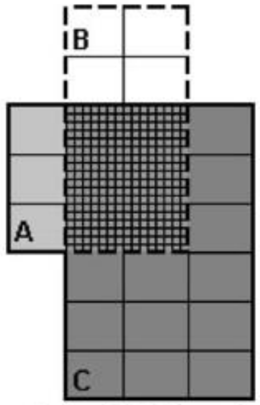
Item utility (IU) (Bruzzese, 2003):

- If we specialize a rule R (A → B) to $A \cup i \rightarrow B$ the confidence may
  - increase when i contributes to an explanation of B,
  - Stay constant when C is redundant to explain B
  - Decrease when the true association was A → B
  - Item utility is the difference of confidence values normalized with the absolute values

$$IU_i = \frac{C_R - C_{R(-i)}}{\max(C_R; C_{R(-i)})}$$

  - Item utility is computed item by item – in contrast to DOC

Interestingness Measures



(From: Bruzzese, 2003):

Left image: B has a positive IU, increasing confidence when added to the LHS A.

Right image: The rule $A \rightarrow C$ has 3 counter examples but $A \cup B \rightarrow C$ has 7 counter examples decreasing confidence

- Item utility is an objective measure for the value of specializing the ancestor with a new item
- A-rules may have high confidence, even if some items on the LHS have low item utility. Thus, item utility + other measures helps to generate truly interesting results.

Ensure high coverage

Subspace clustering - highly ranked subspaces are often similar and partially redundant.

→ The selection of the most important subspaces should consider coverage, i.e. return complementary information that is representative.

Association rule space: Instead of just assessing each rule independently, some measures consider a whole *set of rules* and return a selection has not necessarily the top scores but involves many items.

For processing, transactions, such as

tomato, cheese, beer
cheese, chips, wine
fish, water, potatoes

Tomato	Cheese	Beer	Fish
1	1	1	0
0	1	0	0
1	0	0	0

are transformed in tables where each possible item is a column and each transaction a row.

If an item occurs in a transaction the cell is assigned one, otherwise zero.

Filtering & Preprocessing

If transaction data is large (thousands of items and millions of transactions), tables are sparse (most entries are zero).

More efficient schemes reduce the memory consumption by compressing the zero entries.

Filtering:

- Initial step before visualization and later used to refine results.
- Primarily based on selected interestingness measure and *thresholds*.
- Rule length may be adjusted such that overly long rules (which probably have low support) are avoided.
- We may also ask for the "topN = Number" rules, e.g. in R. and thus control how many rules are displayed.

Result:

- A set of rules with involved variables, support (relative and as absolute numbers).
- Rules are sorted according to a selected interestingness measure or a combination thereof.

Sorting:

- While some interestingness measures are used for filtering, often others may be used for sorting the remaining rules.
- Lift and itemlength are typcial sorting criteria.

In medical data, rules with high lift indicate strong risk factors.

Filtering & Preprocessing

Rule antedecedent			Participants supporting antecedent	Target class of the rule	Participants supporting the rule		Rule confidence
Variable 1	Variable 2	Variable 3			absolute number	percentage in class	
som_waist_s2 $\leq$ 80	-	-	132	A	132	52 %	100 %
som_bmi_s2 $\leq$ 24.82	-	-	109	A	109	43 %	100 %
som_huef_s2 $\leq$ 97.8	-	-	118	A	117	46 %	99 %
stea_s2 = 0	-	-	218	A	214	84 %	98 %
stea_alt75_s2 = 0	-	-	202	A	198	78 %	98 %
stea_s2 = 1	gx_rs11597390 = 1	age_ship_s2 > 59	20	B	17	40 %	85 %
stea_alt75_s2 = 1	hrs_s_s2 > 263	age_ship_s2 > 59	20	B	17	40 %	85 %
stea_alt75_s2 = 1	hrs_s_s2 > 263	ldl_s_s2 > 3.22	20	B	17	40 %	85 %
stea_s2 = 1	age_ship_s2 > 66	tg_s_s2 > 1.58	17	B	14	33 %	82 %
stea_s2 = 1	age_ship_s2 > 64	hrs_s_s2 > 263	17	B	14	33 %	82 %
gluc_s_s2 > 7	tsh_s2 > 0.996	-	6	C	6	35 %	100%
som_bmi_s2 > 38.42	age_ship_s2 $\leq$ 66	asat_s_s2 > 0.22	6	C	6	35 %	100%
som_bmi_s2 > 38.42	sleeph_s2 > 6	blt_beg_s2 $\leq$ 38340	6	C	6	35 %	100%
som_bmi_s2 > 38.42	sleeph_s2 > 6	stea_s2 = 1	6	C	6	35 %	100%
hrs_s_s2 > 371	sleepp_s2 = 0	ggt_s_s2 > 0.55	6	C	6	35 %	100%

All rules have up to three variables on the LHS. Rules serve to classify the target variable (fatty liver, category A, B and C). Rules are grouped according to LHS length

(From: Niemann, 2014).

Exploration of Rule Spaces

- Rule spaces need to be explored by means of grouping, operations on rules, and visualization.
- Grouping:

  For a rule ($A \rightarrow B$), a set of rules can be generated by applying one of the following operations (Jorge, 2002)

  – Generalization of A, i.e. remove items $A \cap \{i_1, \ldots, i_n\}$
  – Generalization of B, i.e. remove items $B \cap \{i_1, \ldots, i_n\}$
  – Specialization of A, i.e. add items $A \cup \{i_1, \ldots, i_n\}$
  – Specialization of B, i.e. add items $B \cup \{i_1, \ldots, i_n\}$

  These rules are checked w.r.t. interestingness values and the interesting rules are presented as one group.

  Group all rules with the same antecessor and consequences.

- Base on group, enable navigation in rule space

Exploration of Rule Spaces

General strategies (Bruzese, 2002):

- **Pruning and Display.** Use various tests, e.g. on statistical significance of antecendents, consequence and confidence to reduce the rule set.
  Display the reduced set and enable detailed analysis.
- **Display and prune.** Present an overview of a large rule space, select subsets graphically and perform pruning.

Information Space:

- The information space contains summary information, e.g. size of the database (row, columns), single most frequent items in a transaction, average number of items in a transactions and
- A set of rules with LHS and RHS and related interestingness values.

Example for a summary:

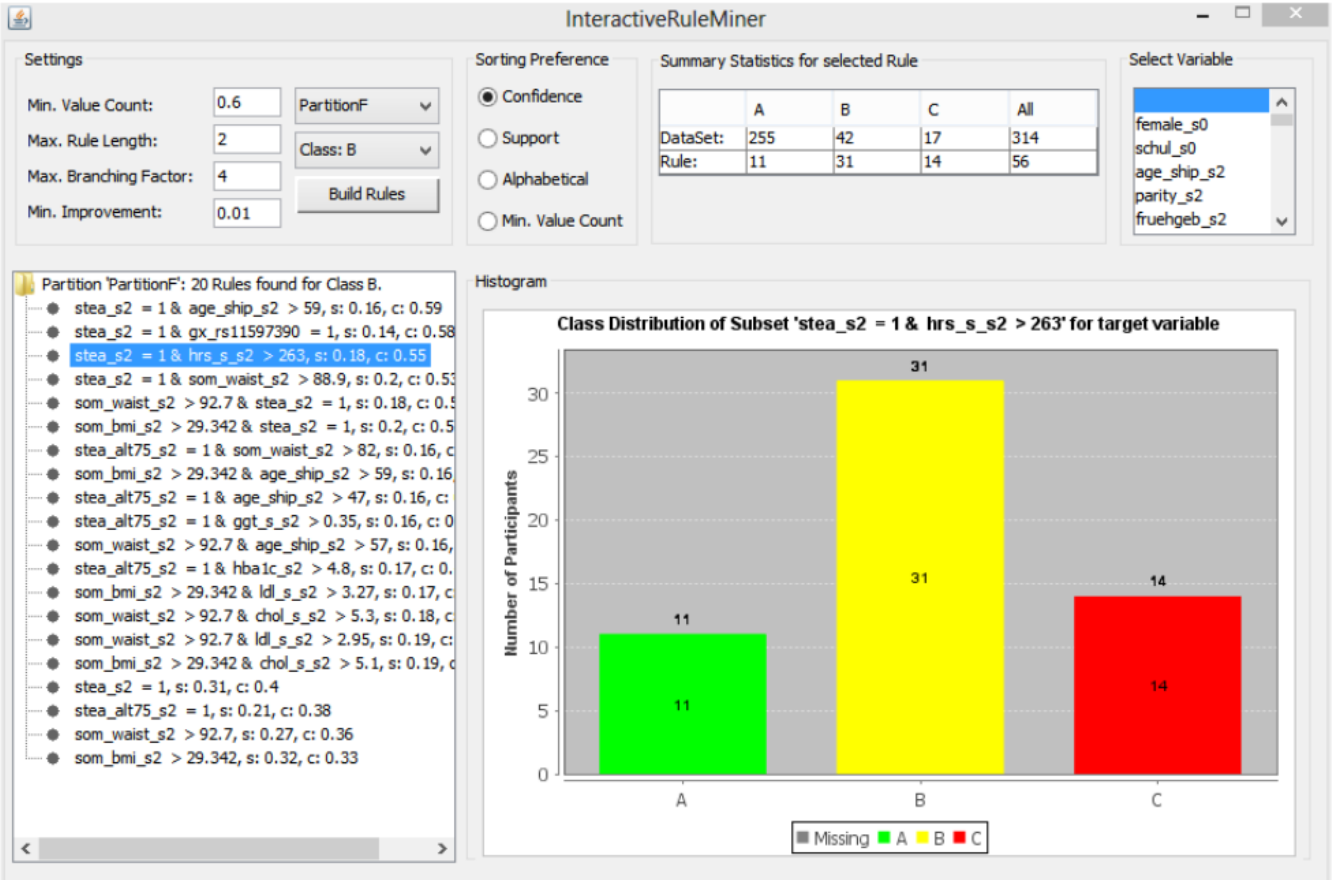
9800 rows, 170 columns, most frequent items: milk: 2510, vegetables 1900, soda 1715, density: 2%

Items per transaction: average 4.8, itemsize 1: 2100, itemsize 2: 1640, … itemsize 10: 240, …

Visualization Techniques: Overview

- *Rule browser*: In datamining/databases, the classic technique to „visualize“ association rules filtered and sorted according to selected interestingness measures.
- Based on InfoVis research, color, size, shape, location of elements can be employed in
  - Table-based views
  - Graph-based views
  - Scatterplot-based views
  - Mosaic plots, and
  - Few 3D visualization techniques
- Integrated systems comprise several vis. techniques in a coordinated manner, e.g. (Sekhavat, 2013)

Visualization Techniques: Rule Browser



For each rule (list view) summary statistics and frequency distribution are presented as context (From: Niemann, 2014).

Interaction Techniques:

Basically all visualizations require facilities

- to pan,
- to zoom in and out,
- to inspect individual rules or sets of rules with numbers representing interestingness values
- to highlight selected rules
- to enable rearrangement of data
- to change filtering and sorting criteria
  - According to interestingness but also to rule length (min, max)

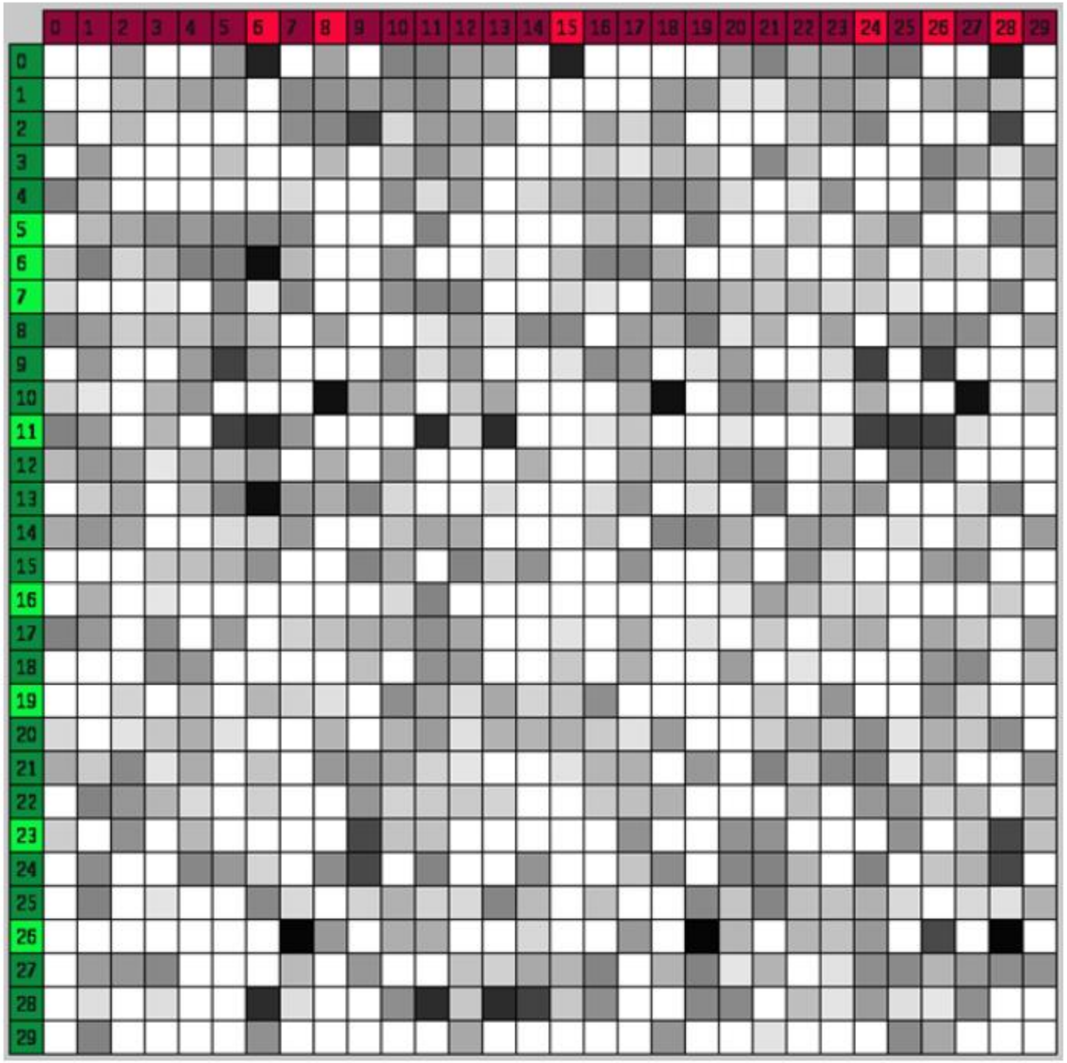
Visualization Techniques: Table-Based

Basic concept:

- A table/matrix is constructed with all LHS-parts of rules as rows and all RHS-parts columns.
- At the intersection of row_i and $column_j$ a glyph represents the interestingness measures in case a rule exists with *i* as LHS and *j* as RHS.
- Otherwise, the *cell (i,j)* remains empty.

Properties:

- Depending on the thresholds for the i-measures, most cells are empty.
- Re-ordering may be performed grouping cells with similar i-values



A table with rows representing LHS and columns representing RHS of A-rules.

Darkness represents confidence (From: Sekhavat, 2013).

Visualization Techniques: Table-Based

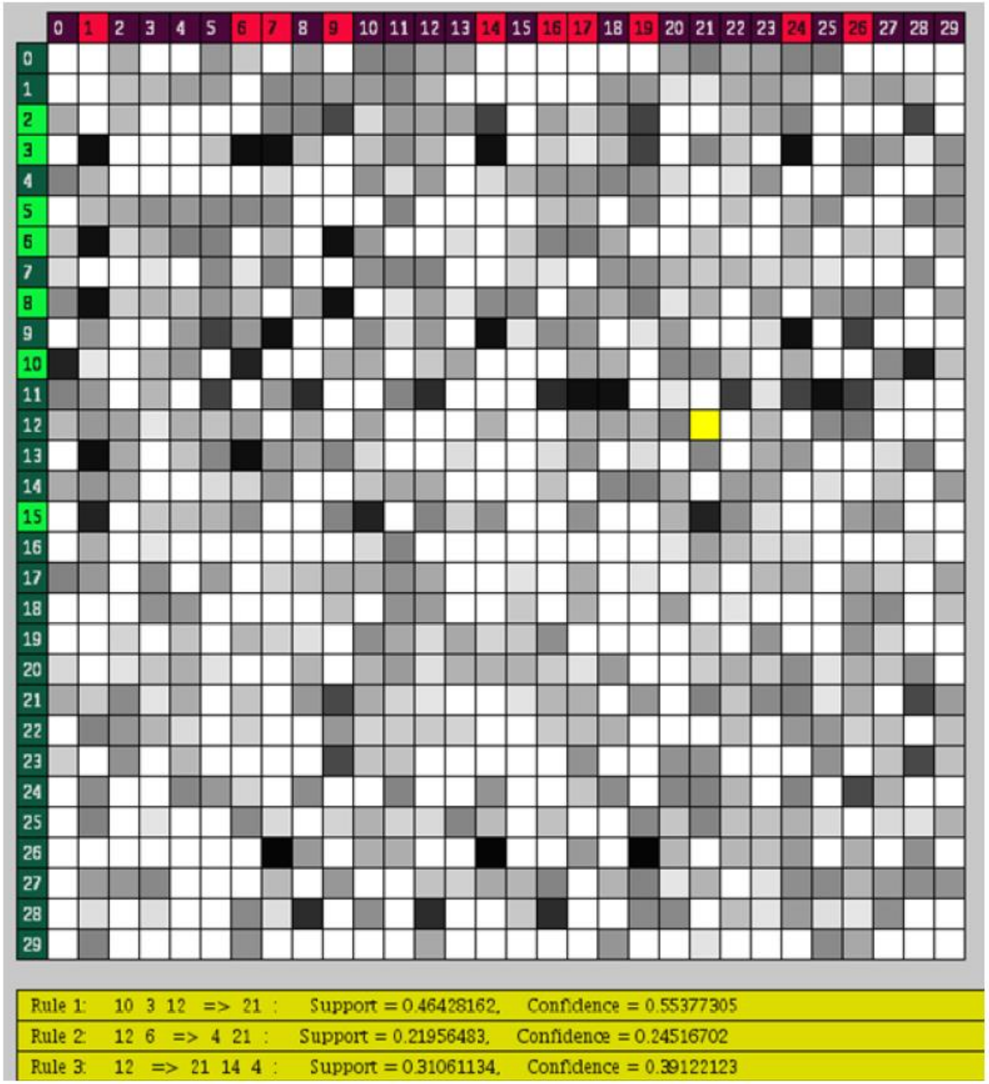
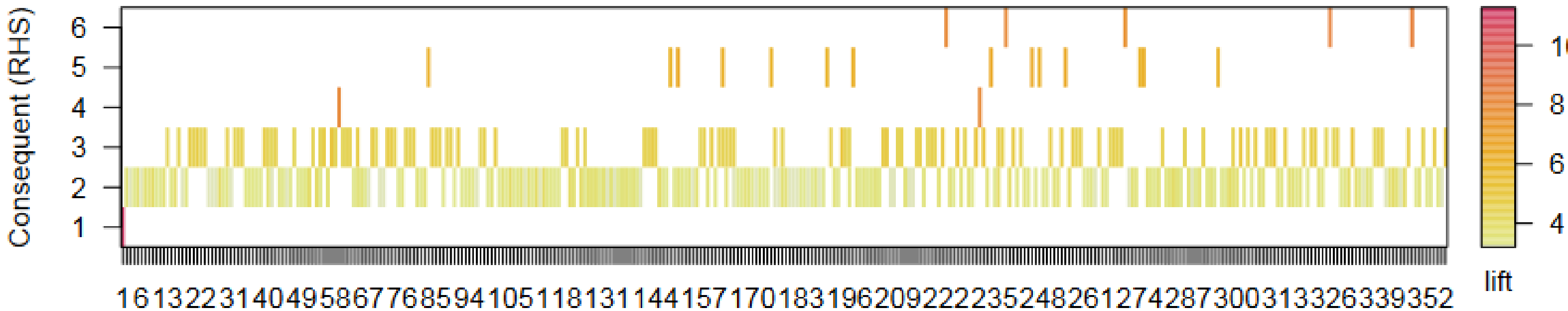
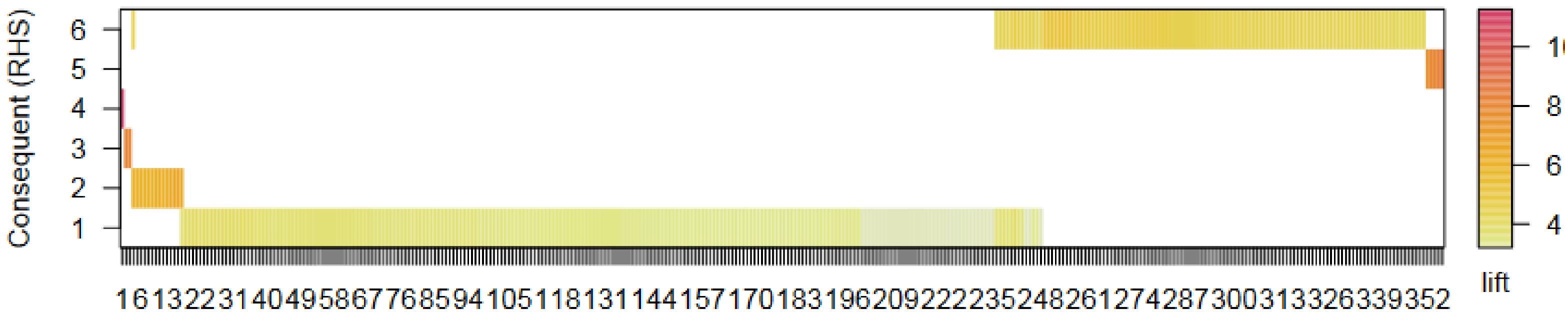


Table-based visualization with an additional text view showing rules related to the selected (yellow) cell, i.e. with (12) being part of LHS and (21) being part of RHS
(From: Sekhavat, 2013).





Re-ordering has a substantial effect on perception of rules. The rules are labeled with numbers, not item names. This eases the layout, but hampers interpretation (From: Hashler, 2011).

Discussion: With bivariate color scales, a further i-measure can be conveyed in table-based and scatterplot-based visualizations.

Visualization Techniques: Table-Based

- For larger itemsets: grouped visualizations
- Grouping is based on clustering involved items
- Degree of similarity is assessed with the Jaccard index (recall clustering:validation)
- Idea goes back to Toivonen, 1995 and was re-used multiple times

Major disadvantage:

- Restricted to binary relations between to two items (one LHS and one RHS item)

Visualization Techniques: Table-Based

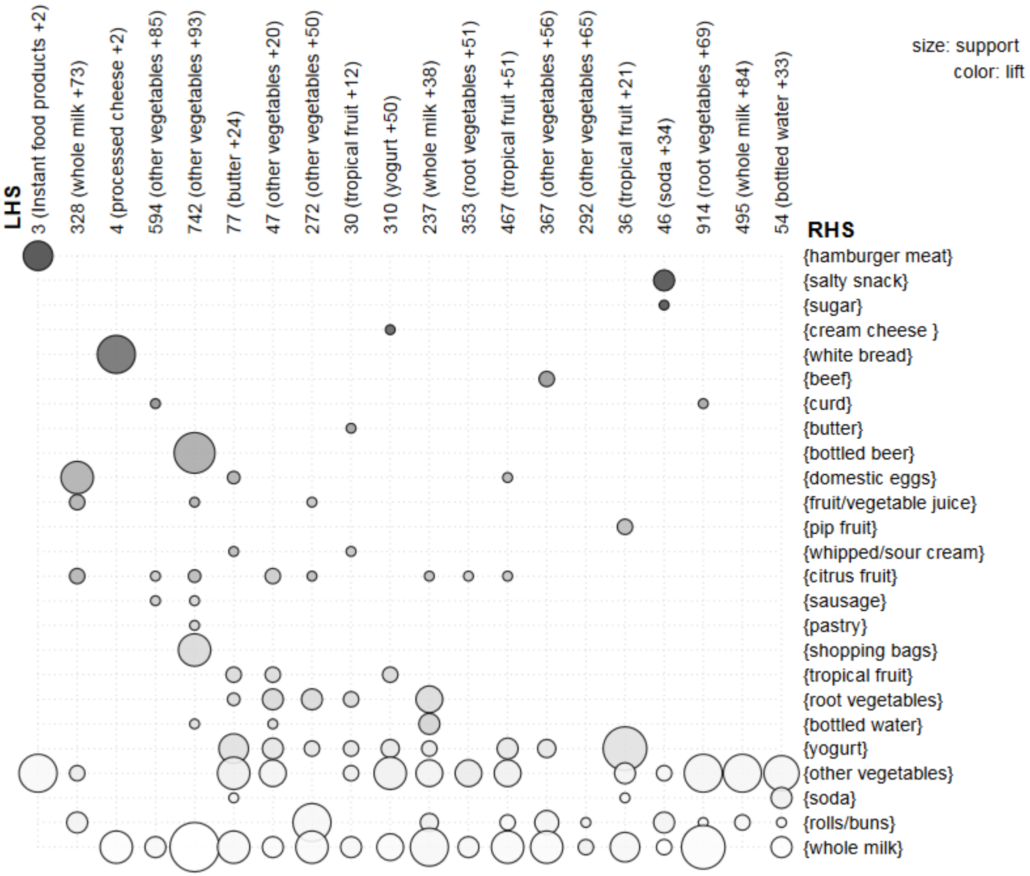


Table-based overview visualization. Color and size of a circle represent two interestingness measures (From: Hashler, 2011b).

Visualization Techniques: Graph-Based

Oldest A-rules vis. technique (Klemettinen, 1994)

Directed Graphs may be used to reveal relations between LHS and RHS of one rule and relations between rules.

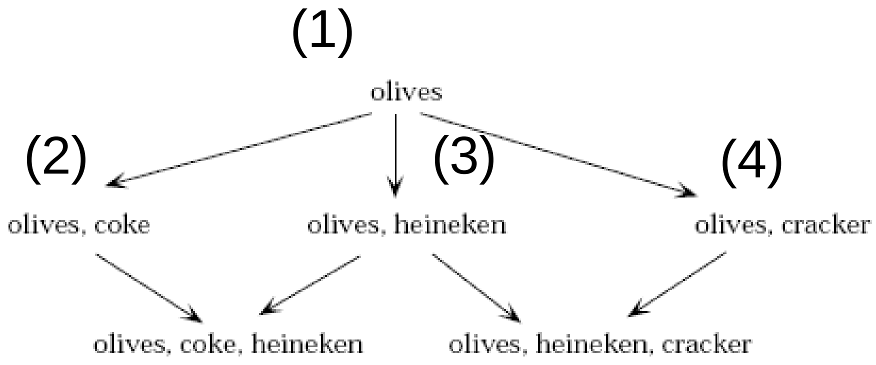
Graph visualizations may encode various properties

- using the color, size, and shape of nodes and
- Using the width and darkness of edges

Application in A-rules vis.: encode interestingness measures and highlight selections (try to support visual scanning activities)

Visualization Techniques: Graph-Based

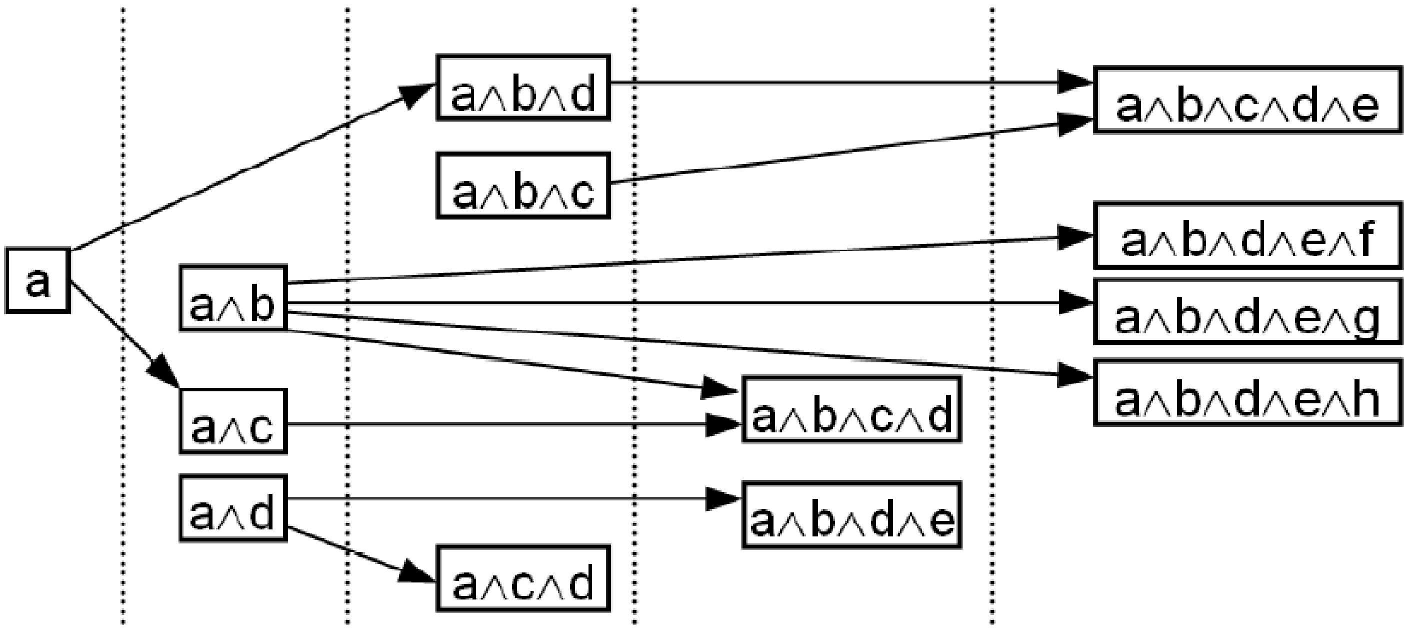
No	left-hand-side of "→ bourbon"	conf.	supp.
1	olives	51.80	24.48
2	olives & coke	73.65	10.89
3	olives & heineken	65.52	13.29
4	olives & cracker	70.81	13.09
5	olives & heineken & coke	61.22	3.00
6	olives & heineken & cracker	77.86	10.89



A set of rules and the related *rule graph* (without using any enhancements). General rules, like 1, are ancestors of more specialized rules

Analysts may ask (cf. Hofmann, 2000):

- Is any 3-item rule better/worse than others?
- Does a more precise LHS lead to a significant increase in confidence?
- How much support we lose with adding an item to the LHS?



A rule graph with column-wise output. Note, that specialized rules may have more than one ancestor. Rule graphs are directed acyclic graphs, no trees (From Blanchard, 2006).

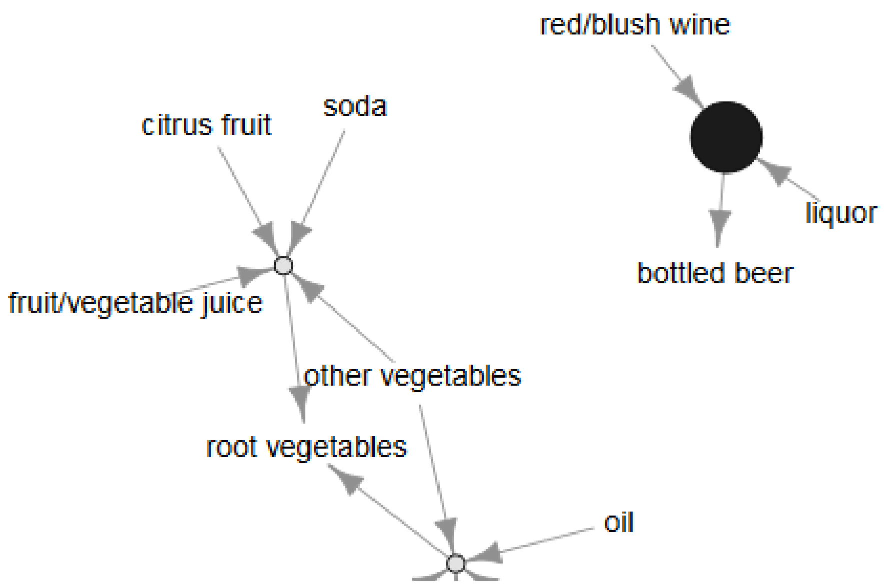
Interactive exploration of rule graphs

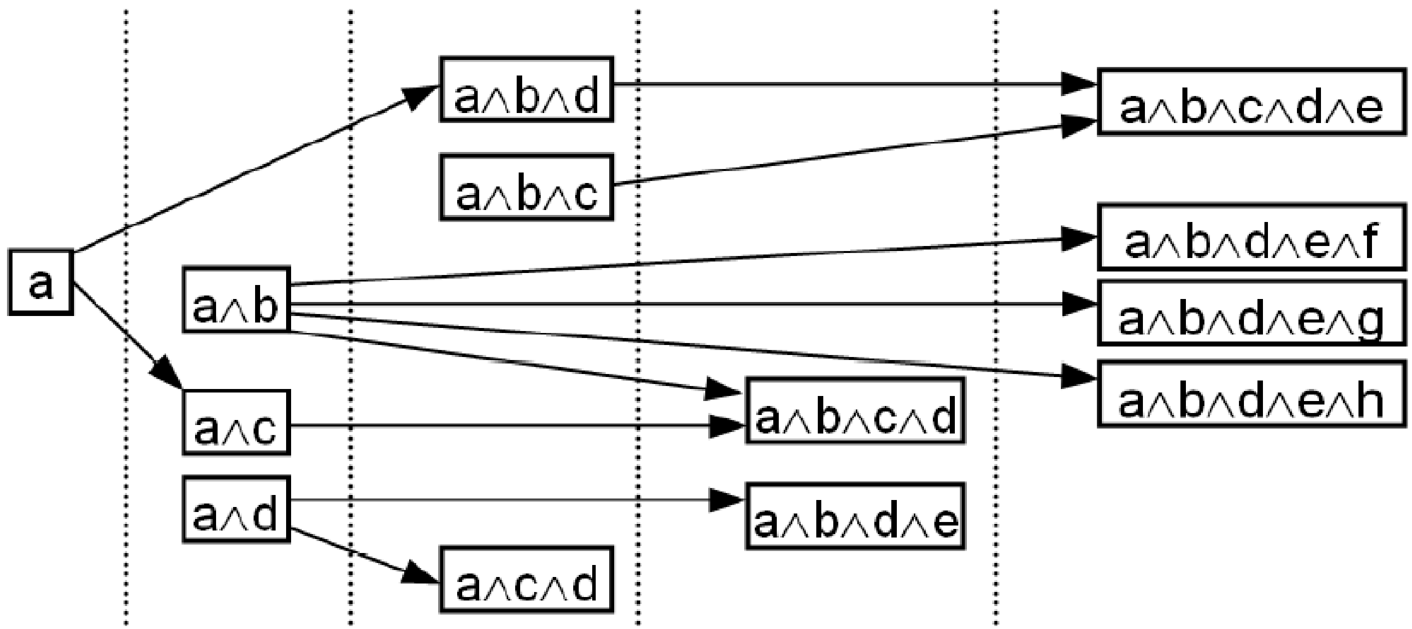
Interaction is performed to navigate in the graphs:

- Select a condition and show all dependent rules (forward chaining)
- Select a condition and show all antecendents

Select rules (edges) and show details of rules in terms of interestingness

Visualization Techniques: Graph-Based





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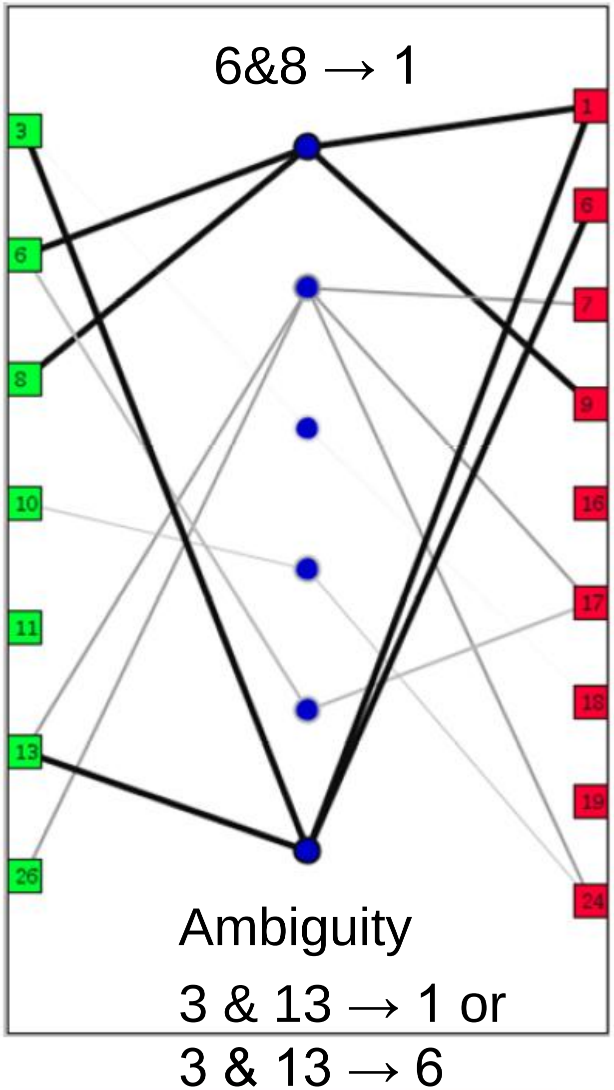


Graph-based view:

- green rectangles represent LHS items,
- red rectangles represent RHS items and
- circles indicate rules.
- Edges encode *support* and *confidence* by means of line width and darkness (From: Sekhavat, 2013).

Visualization Techniques: Graph-Based

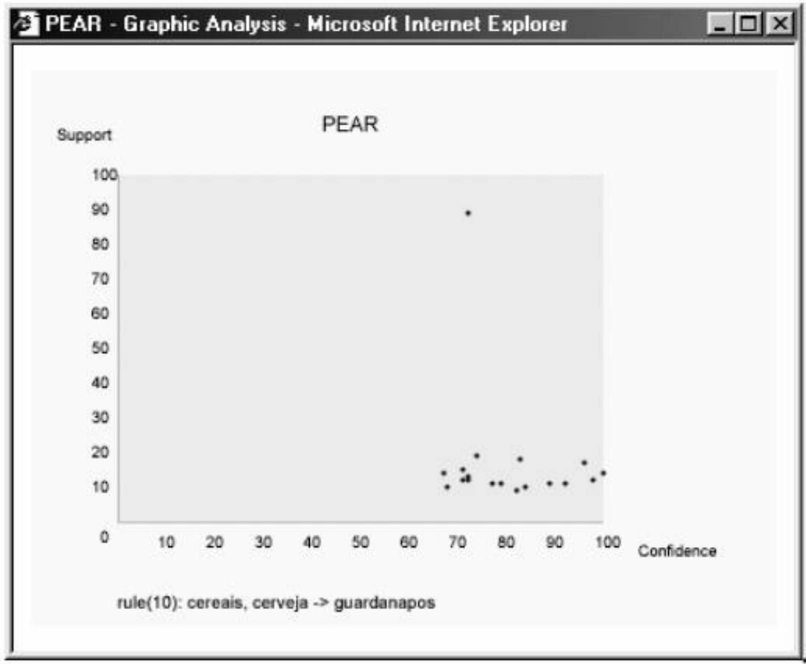
Graph-based techniques

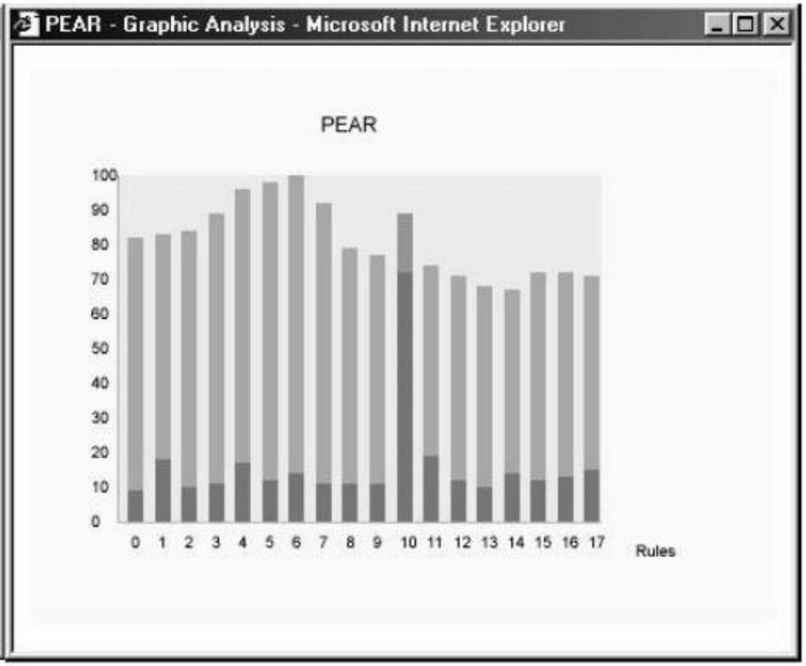
- may represent one-to-one, many-to-one and many-to-many rules (compare with matrix-based views)
- Are restricted to a small set of rules

Application: After selecting subsets of rules, e.g. in other visualizations, graph-based techniques reveal specific properties

Visualization Techniques: Scatterplot-Based

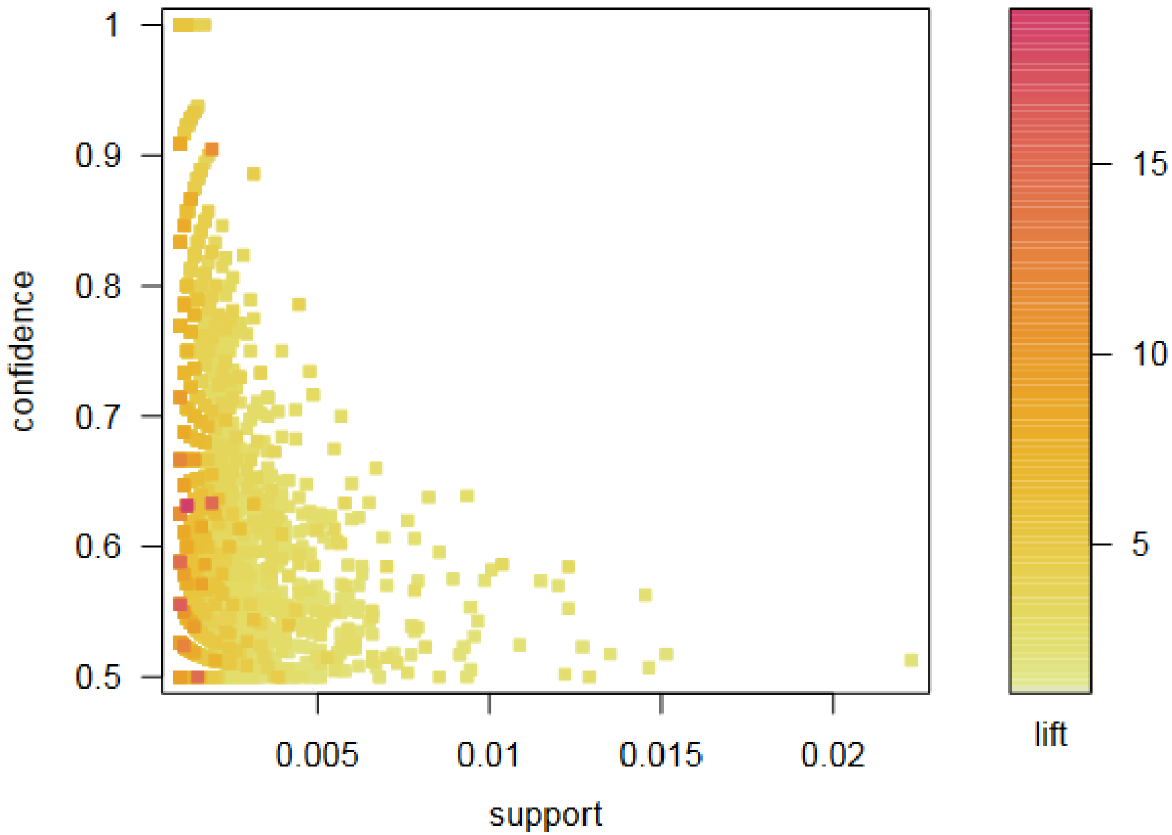
Traditional 2D scatterplots present overviews of rules w.r.t. 2D interestingness measure, e.g. support and confidence.





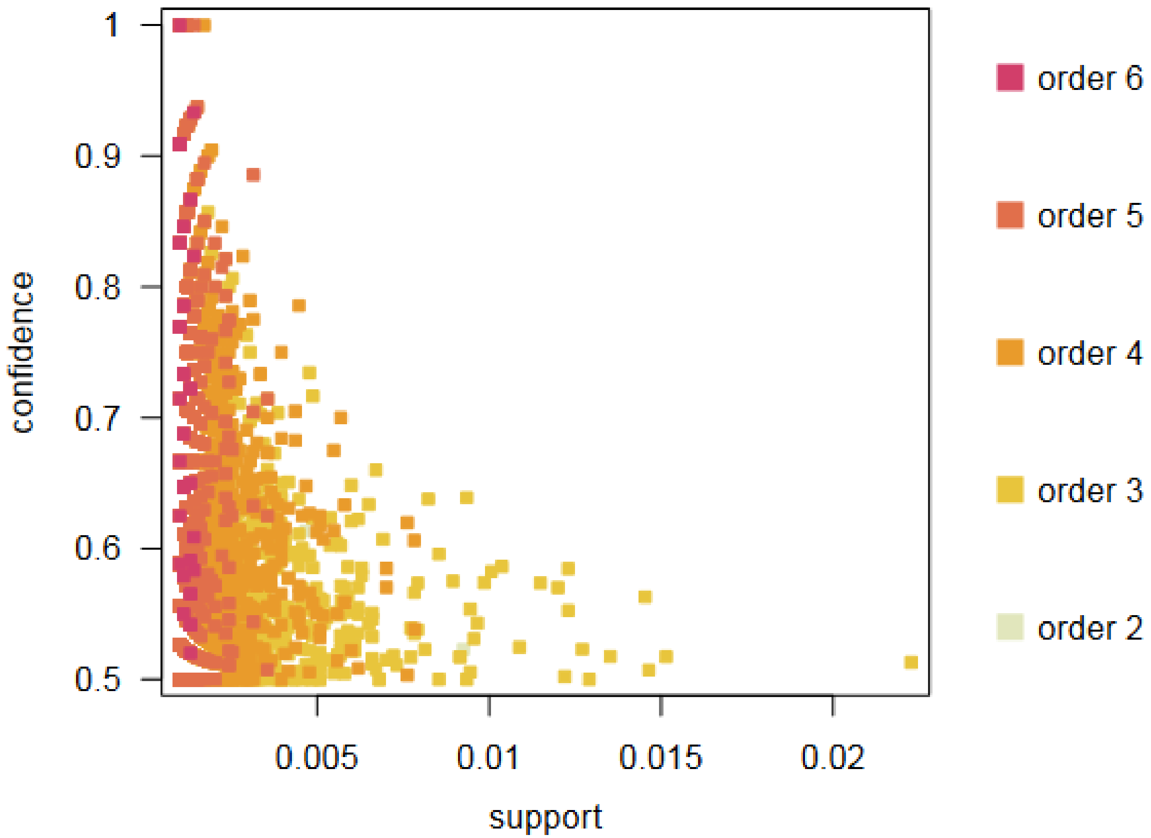
A scatterplot and a histogram indicate interestingness measures for a subset of rules (From: Jorge, 2002)

Visualization Techniques: Scatterplot-Based



Position (x, y) and color are used to represent three properties of association rules in an overview. Rules with high confidence tend to have little support. Rules at the right border are often very interesting (From: Hashler, 2011b)

Visualization Techniques: Scatterplot-Based



A special variant of scatterplots, called Two-key plot, indicates the length of the rules as color (Unwin, 2001).
Note the inverse relationship between *order* and *support*.
Image taken from (Hashler, 2011b).

Visualization Techniques: Scatterplot-Based

Interaction:

- Select rules via brushing (rectangle or other shapes)
- Selected rules may be shown in a textbrowser
- Adjustment of cut-off points for all interestingness measures

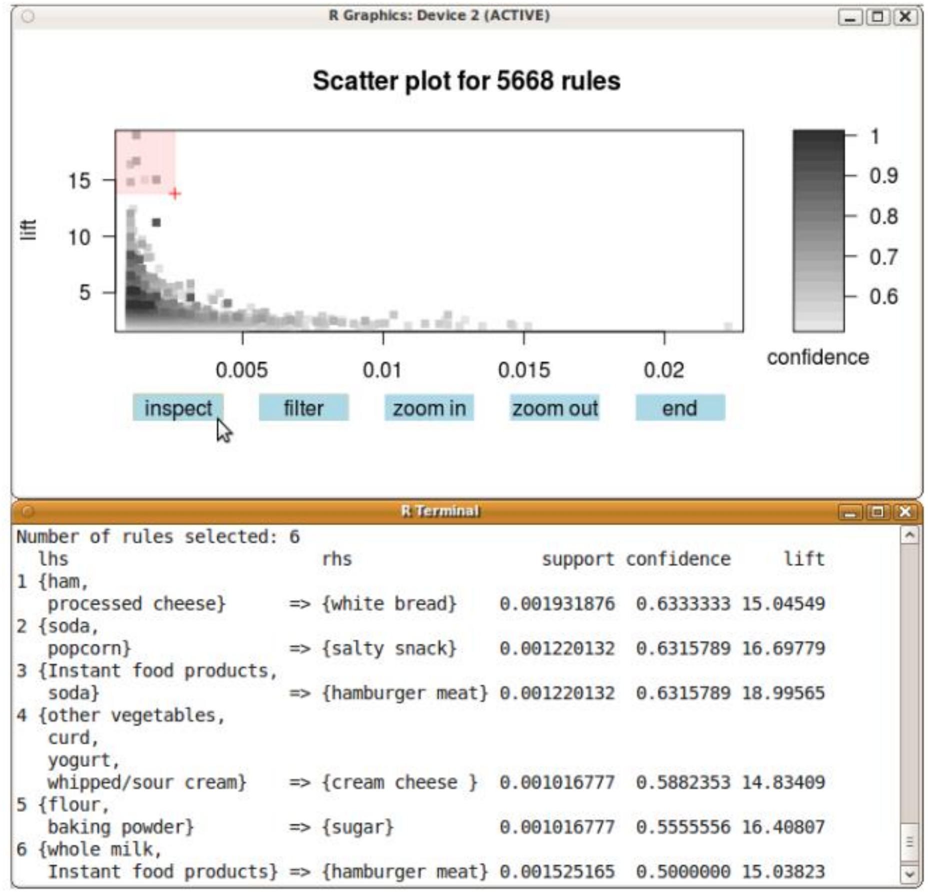


Image taken from (Hashler, 2011b).

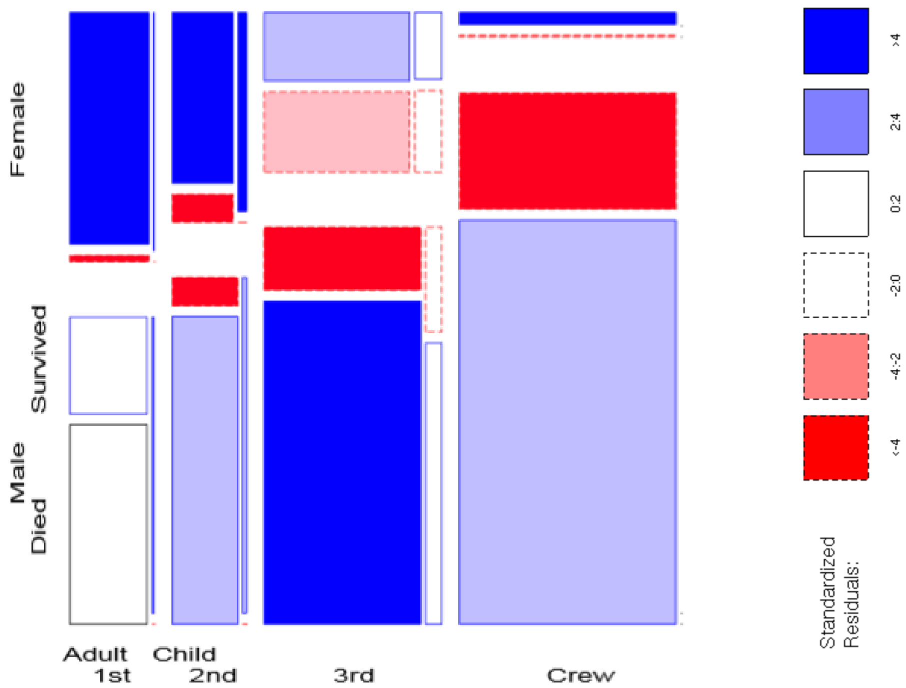
Scatterplot-Based techniques

- Give an overview over many rules w.r.t. 2-3 interestingness measures
- Do not provide details about the LHS, RHS of a rule
- Are used to select subsets to be displayed as table- or graph-based visualizations

Visualization Techniques: Mosaic Plots

- Mosaic Plots visually display contingency tables (recall Visualization Lecture, InfoVis).
- A rectangular display is splitted alternatively horizontally and vertically to convey how often a condition is fulfilled or not (Titanic example: woman, man, children, first, second, third class, survived yes/no)
- The area of the rectangles indicates frequency.

Visualization Techniques: Mosaic Plots



Recall from Vis. lecture: For the three variables Gender, Age and Class survival is indicated. Females, children and first class passengers had a higher survival chance (From: Friendly, 2000)

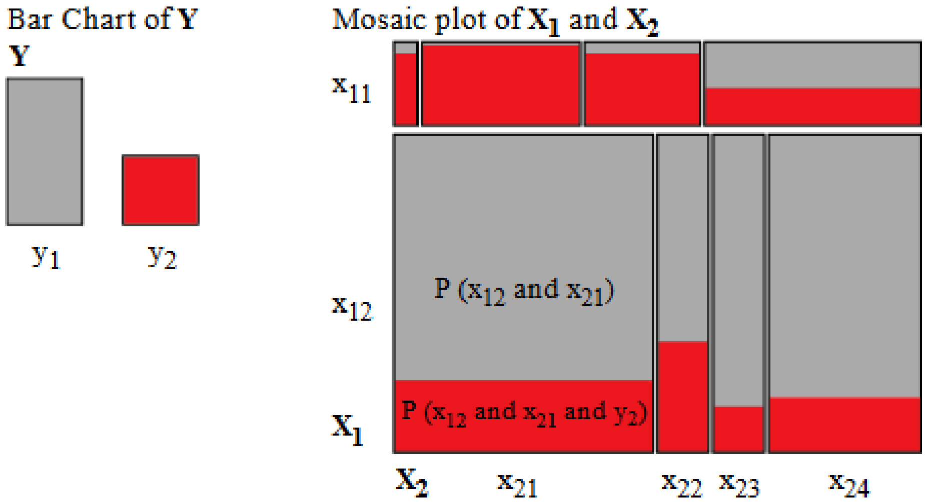
Visualization Techniques: Mosaic Plots

For an association rule, $A\,(x_1, \ldots, x_n) \Rightarrow B(y)$

a mosaic plot may be constructed that reveals all LHS items $(x_1, \ldots, x_n)$ and their distribution. For each combination of LHS items, the portion that fulfils the RHS (B = y) may be highlighted.

Width and height of the highlighted area reveals the confidence and support of all association rules involving (a subset of) $(x_1, \ldots, x_n)$ and y (Hofmann, 2000)

Visualization Techniques: Mosaic Plots



Mosaic Plot of attribs. x_1 and x_2 (with two and four possible values). The bar chart reveals the distribution of the binary variable y to y_1 and y_2 .

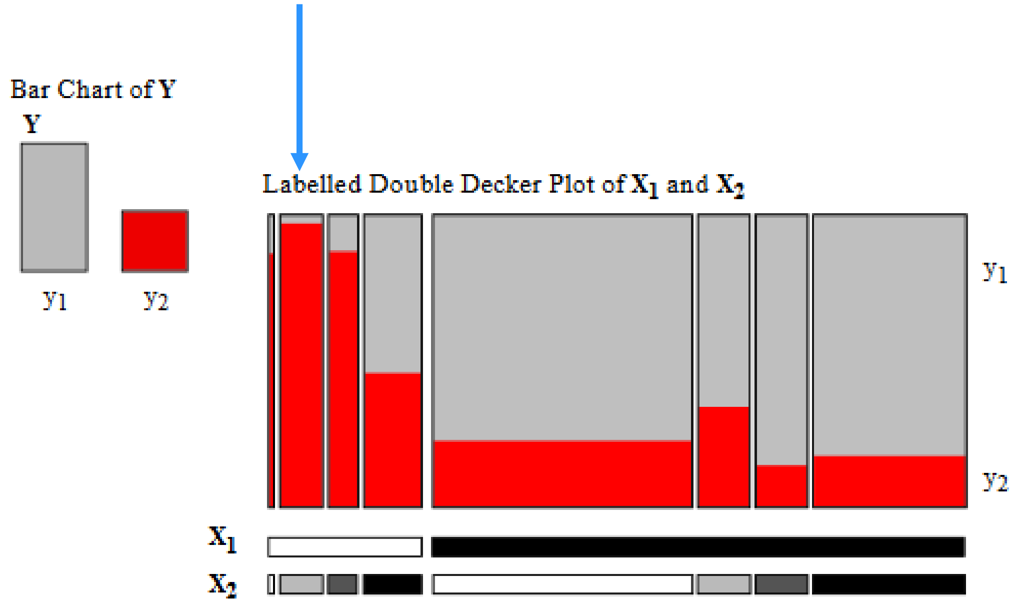
The portion of $y = y_2$ is highlighted in the mosaic plot.

Visualization Techniques: Mosaic Plots

Disadvantage: comparison of sizes is difficult due to the alternative horizontal/vertical splitting.

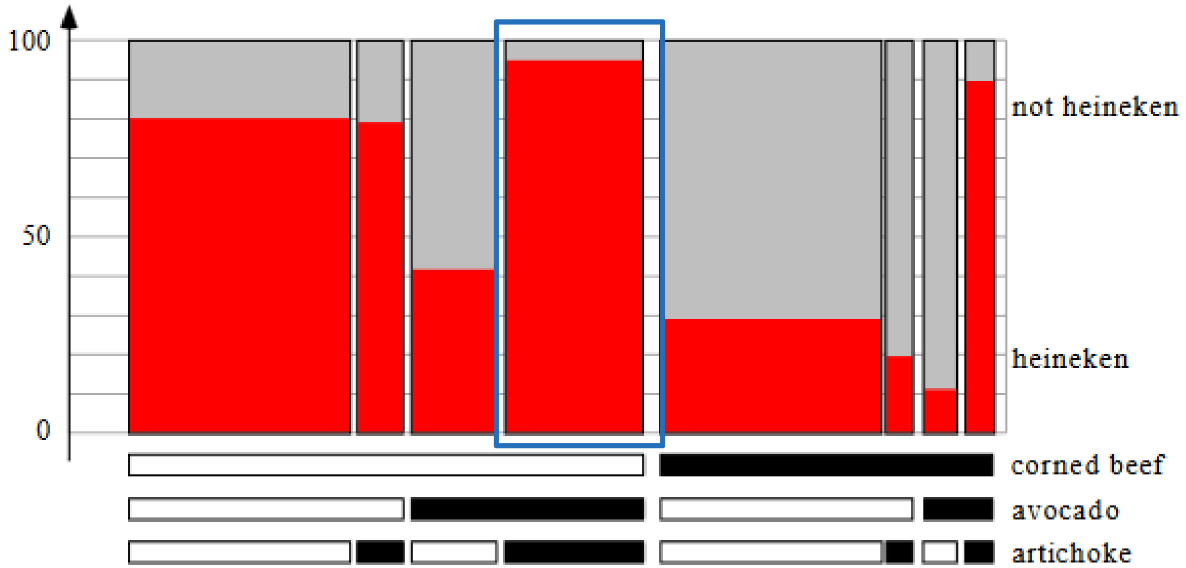
Modification: Use horizontal splitting only, called Double Decker plot. (Only) highlighting splits bin vertically. (Hofmann, 2000)

Width equals support of the rules (narrow rectangles represent rare features) and height equals confidence. For binary variables, confidence should be significantly above 50%.



Double Decker plot related to the previous example. Best AR emphasized (From: Hofmann, 2000).

A textual view with the related rules and the interestingness measure could be added.



An example from basket analysis. Most interesting rule:

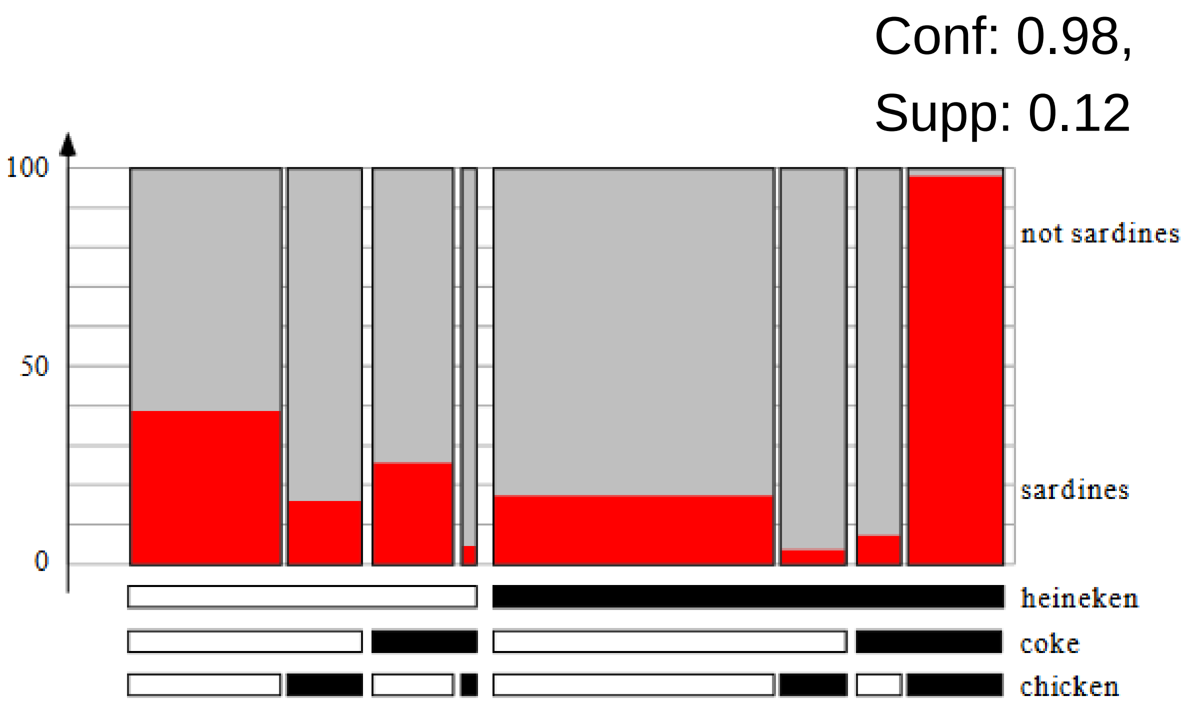
¬corned beef & avocado & artichoke → heineken

corned beef & avocado & artichoke → heineken

has a similar confidence, but much lower support (rare)

(From: Hofmann, 2000)

Visualization Techniques: Mosaic Plots

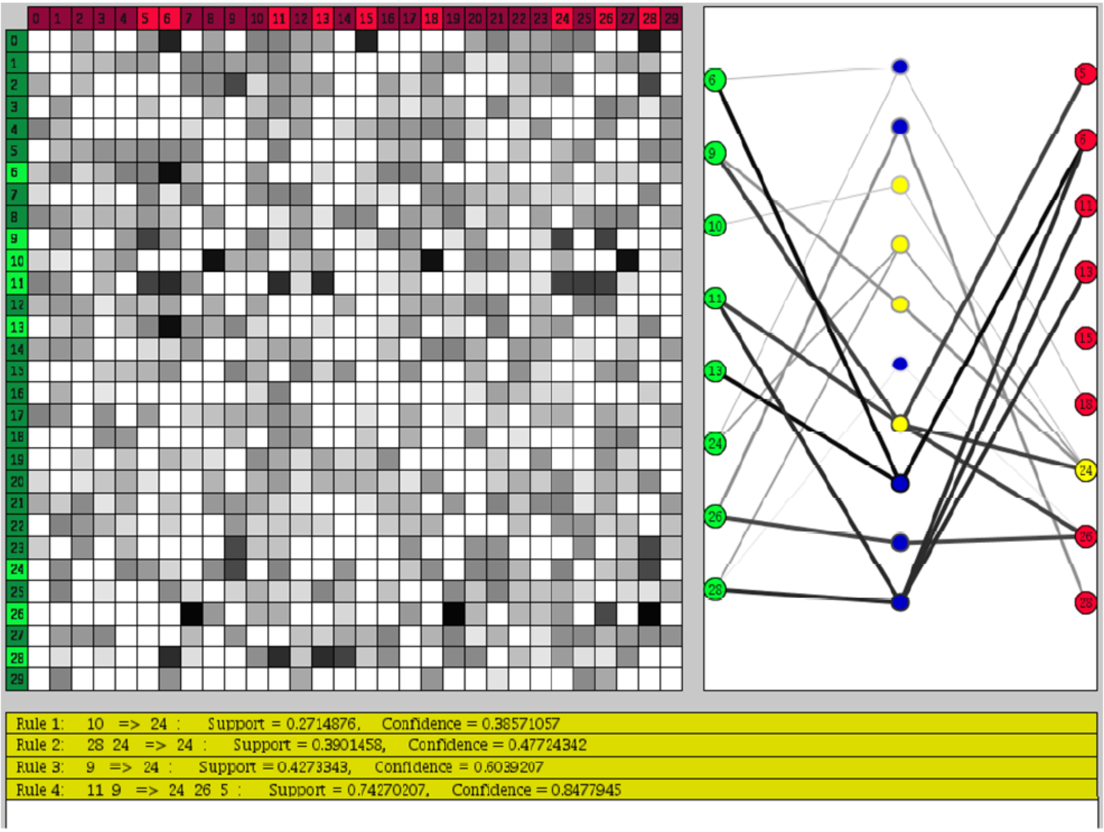


Another double decker plot:

Heineken & coke & chicken → ⌐*sardines*

has a very high confidence, much higher than any other rule related to the same items.

Interestingness could be shown with tooltips (From Hofmann, 2000).



Integrated A Rules visualization.

Based on filtering, a table-based view is created.

Selection of a cell leads to a graph view of all related rules.

Row and column headings are emphasized.

Selection of an LHS or RHS item (24, right) leads to a further refinement, presented textually (below the table). (From: Sekhavat, 2013).

Visualization Techniques: Integrated Views

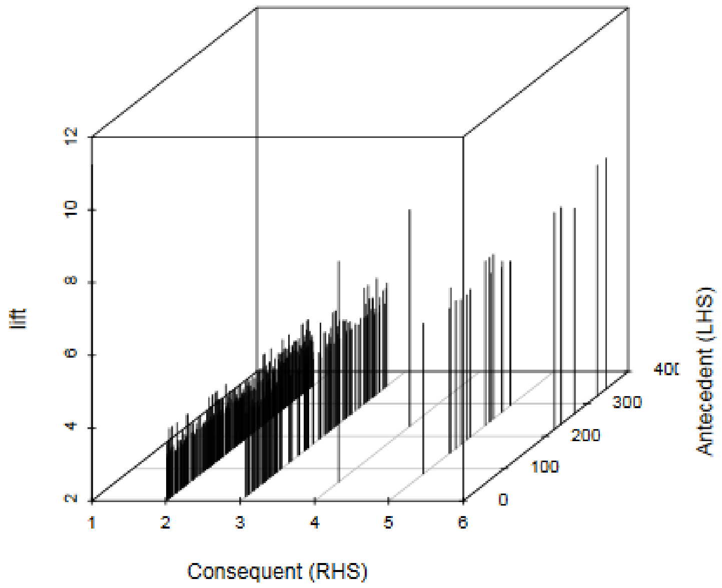
- Integrated views enable focus+context visualizations.

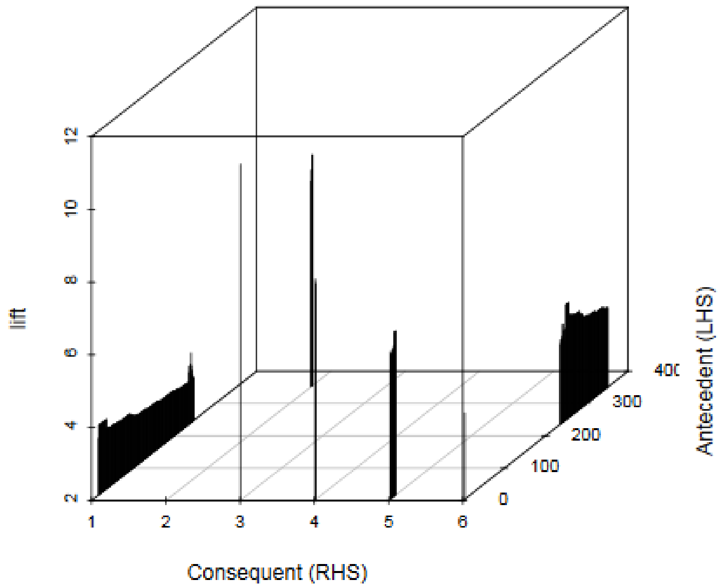
„Integrated“ means:

- selections in overviews enable detailed exploration in related views (brush and link) and
- Highlighting of related items in the overview

Rule mining frameworks should further provide history mechanisms and bookmarking (Blanchard, 2006)

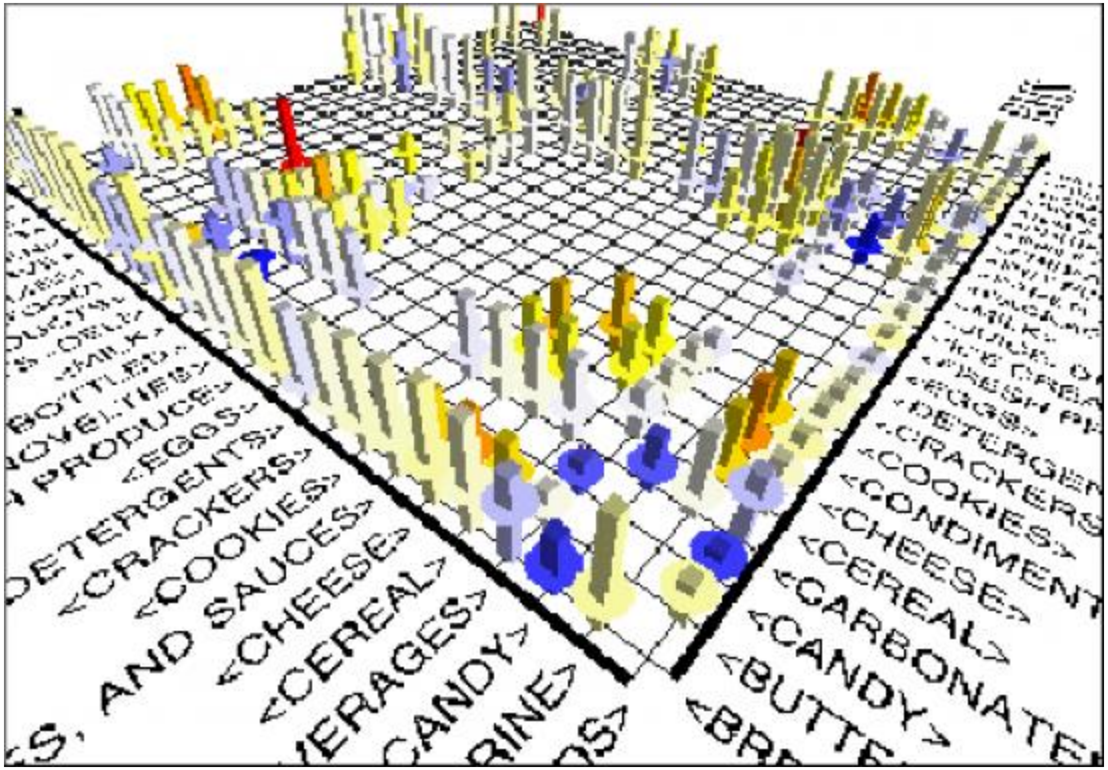
- Matrix-based visualizations may be extended to 3D
- Interestingness may be mapped to height. Interpretation is difficult and requires rotation.





3D matrix-based visualizations (before and after re-ordering) (From: Hashler, 2011)

Visualization Techniques: 3D



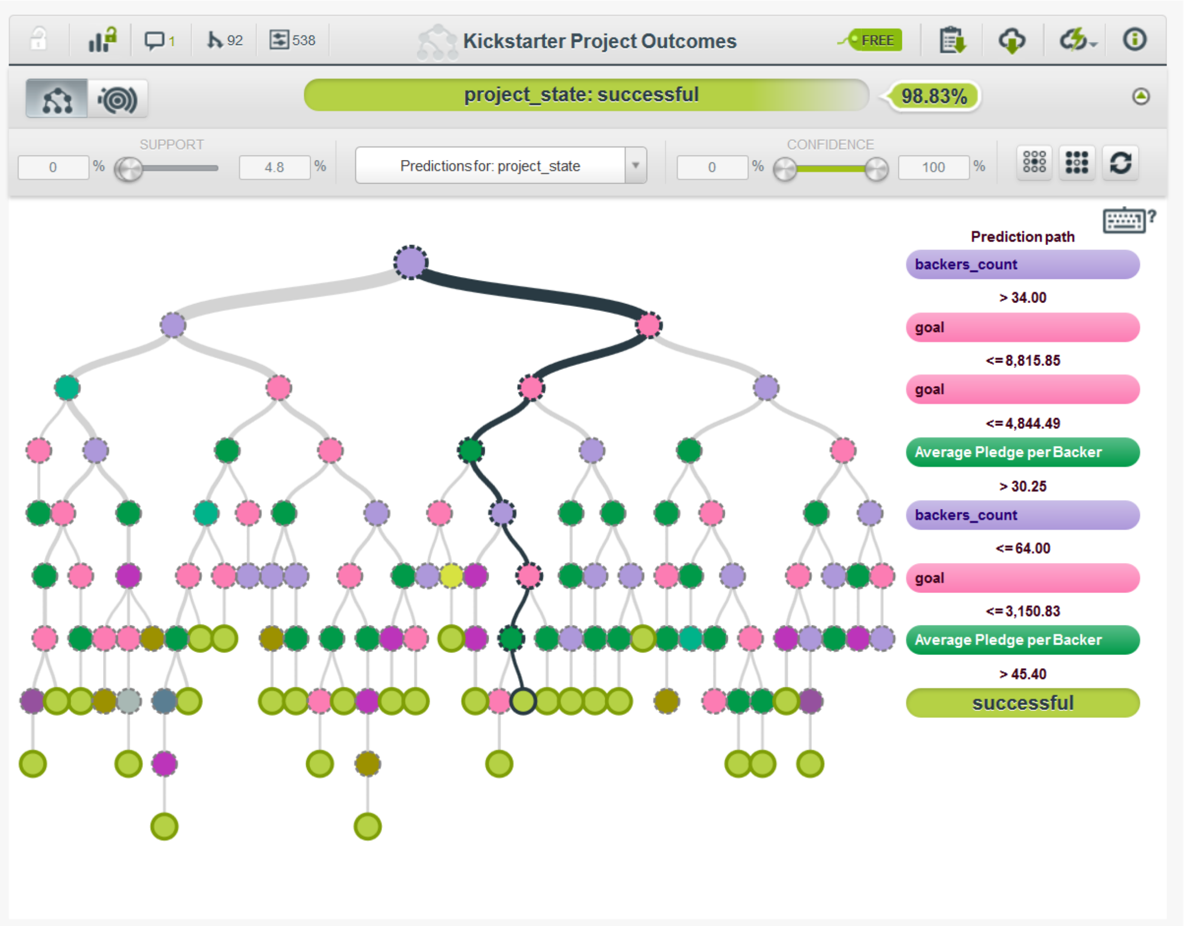
3D bar charts indicate 1:1 rules with hight, color and other attributes to reflect interestingness measures (Screenshot from SGI/MineSet 3.0, ~ 1996)

Visualization Techniques

Advanced methods: Assoc. Rules may be clustered according to the items involved.

Visual exploration (overview) may be guided by cluster visualizations

Interactive Visualization



Rules displayed in a tree, thresholded via support and confidence (From: Link)

Evaluation

- Different visual representations and variants exist, leading to the question which one is most effective.

User studies (e.g. Sekahvat, 2013)

- involve different sets of rules (different sizes of rule sets, scaleability),
- involve task completion time, error rates, confidence and ease of use.

They are performed to assess how users can extract interesting rules,

Impact on real decisions is even more important.

Software

- AR mining is part of major statistics and data mining packages, e.g. SGI‘ MineSet (developed in the 1990s), SAS Enterprise Miner, the Arules and ArulesViz packages of R (Hashler, 2011a)
- Weka provides the HotSpot algorithm that returns classification rules and provides a grouping of numerical values that leads to maxiumum support of these rules (Niemann, 2014)

Summary

- Association rule mining is an *unsupervised learning* approach for categorical data
- Association rules need to be filtered w.r.t. *interestingness* and explored w.r.t. their relations
- Matrix views, graph views and parallel coordinates may be employed to visually support association rule mining
- Driving/Major application: Market basket analysis

(Introductory video)

Outlook

Many techniques are available to visualize classic static A-rules related to categorical data.

For advanced A-rules, such as dynamic, quantitative and weighted A-rules, new interactive visualizations are required to understand their nature.

Dynamic rules are essential to understand how preferences for products or prevalence of symptoms and diseases change over time.

Scenario: Database is (incrementally) updated.

Visualization should indicate how the confidence, support, lift, … change over time highlighting rules where changes are significant (Ong, 2003)

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