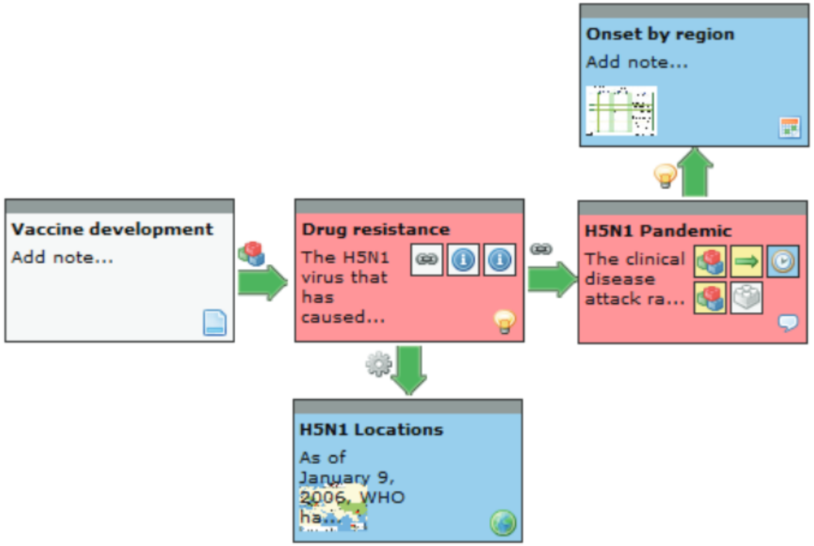
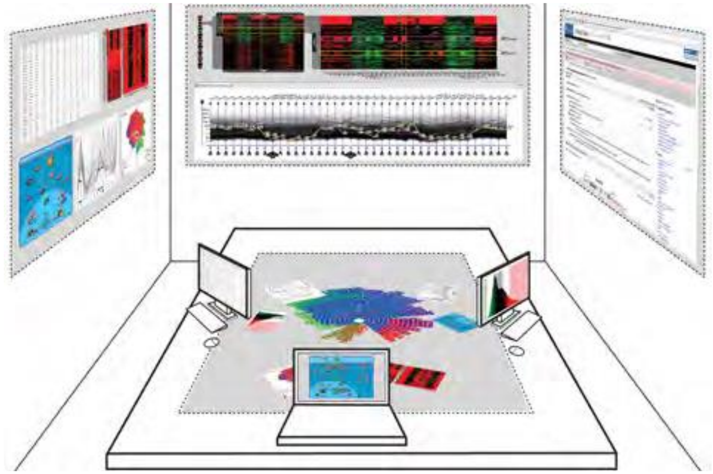
Interactive and Collaborative Visual Analytics





Outline

- Visual Analytics as Interactive Processes
- Collaborative Visual Analytics
  - Cooperative Work
  - Requirements for Collaborative VA
- Co-Located Cooperative VA
  - Hardware Support (displays, input devices, …)
  - Applications
- Distributed Cooperative VA
- Asynchronous Cooperation
- Pair and Group Analytics
- Evaluation

Visual Analytics as Interactive Processes

„Interaction should not be an after thought – a set of controls bolted on a clever visual display to allow the user to modify it – but the first thing to consider.“ (Pike, 2009)

Interaction in Visual Analytics occurs at different levels (Pike, 2009):

- Manipulation of controls in a GUI (low level interaction)
- Interaction with the problem space (high level)

Interaction

- involves *perception* and *cognition*
- is crucial for the ability of a system to support *problem solving* and *decision making*.

VA tools need to *fit in the context*, e.g. a fitness tracking application should not severely interrupt life routines.

Visual Analytics as Interactive Processes

Challenges (derived from Pike, 2009 and):

- Complex problems involve the use of different tools (visual analytics, statistics, presentation) → seamless integration
- Role and tasks of users need to be considered → in-depth user and task analysis to understand the goals, context, constraints.
  - Users may be observers, interactors, discussion leaders, …
- Since goals are often unstable, flexibility is essential. → Flexibility may enable *breakdowns*, situations where the user fundamentally reconsiders thoughts, tools and gets insights.

Software developers *focus on tools*.

Users *focus on problems* that follow them from tool to tool.

VA is used on mobile devices, laptops, PCs up to wall-sized displays.

Interfaces depend on display type (Buering, 2006; Kim, 2007):

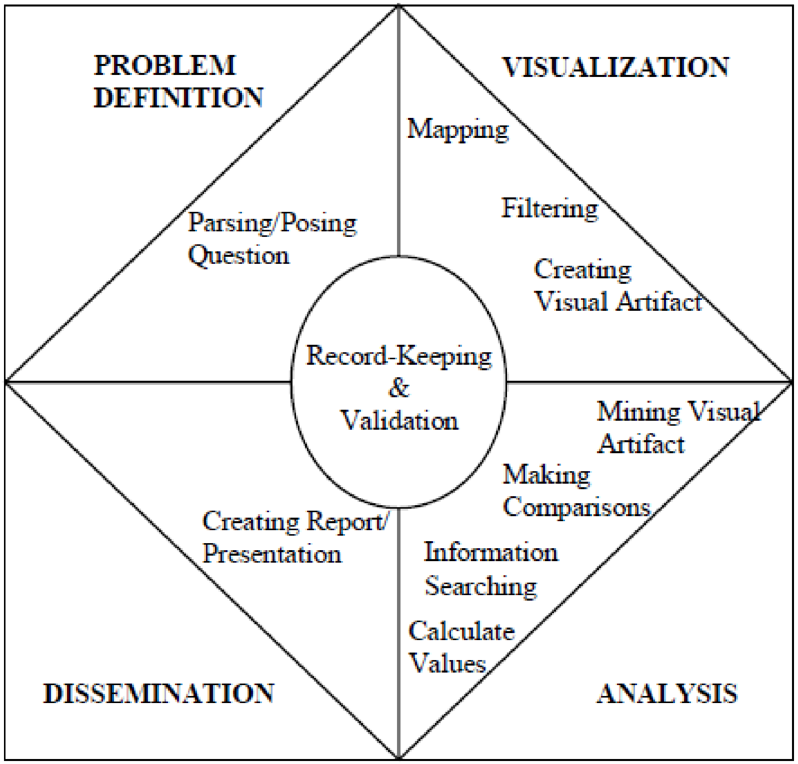
- Appropriate selection on small and large displays differ
- Pure zoomable interfaces are often appropriate for middle-sized to large displays. Fisheye views may be better for small displays.
- Small multiples are useful for middle-sized displays, not for large displays.

Visual Analytics as Interactive Processes

Stages of a VA process: (derived from Pike, 2009 and Mayhar, 2013)

- **Familiarization**: reviewing the data, identify gaps, deter-mining methods to analyze the data, refine the problem
  - In case of follow-up data: compare to previous data
- **Analysis**:
  - Searching, making comparisons
  - Calculate derived values, e.g. descriptive statistics
  - Consider assumptions (e.g. confounders) and hypothesis to test
  - Hypopthesis testing: select the most likely explanations
- **Dissemination**:
  - Preparation of a report, presentation

Visual Analytics as Interactive Processes

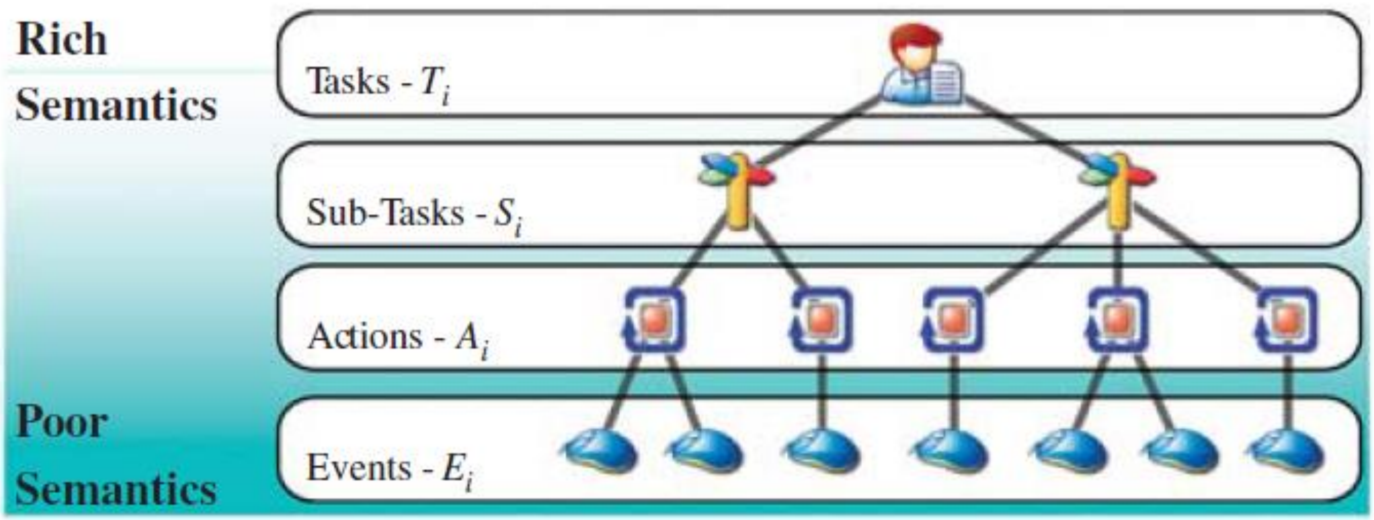


Stages of a VA process as a basis for designing support for cooperation. Central role of record-keeping (note taking, saving charts and other visual representations) (From: Mayhar, 2013)

Visual Analytics as Interactive Processes

Levels of Interactive Processes (also in VA):

- Tasks,
- Subtasks,
- Actions, and
- Events



The hierarchy of intent and actions (From: Gotz, Zhou, 2009)

Visual Analytics as Interactive Processes

Example (derived from Gotz/Zhou, 2009)

- **Task**: Identify key market insights to generate investment recommendations.
- **Subtasks**:
  - Characterize the overall 52-week market trend in the technology sector.
  - Identify the best and worst performing financial companies over the last 8 weeks.
- **Actions**:
  - *Query* for 8 weeks worth of stock market data.
  - *Split* companies by sector.
  - *Filter* to show only the financial sector.
  - *Sort* companies by their changes in stock price.

Visual Analytics as Interactive Processes

UI design principles, particularly important for VA (Pike, 2009):

- Increase the predictability of events,
- Identify long sequences of repetetive actions to replace them with shortcuts
- Reduce interface complexity
- Provide history (provenance) to preserve inquiry paths
- Layout, color schemes, zoom level, applied filters, … should be stored for later re-use in similar cases.

„A closer coupling between understanding the reasoning process … in the user ‘s manipulation and the design of that interface can lead to … systems that better align with the user ‘s goals.“ (Pike, 2009)

Visual Analytics as Interactive Processes

Design critique

- UI design – as a design task – benefits from design critique.
- Sketches, mockups and storyboards are critically discussed with peers.
- Design critique is essential to VA system design as well (Pike, 2009).
- Particular relevance: dashboard design, workflow design, general layout and interaction design, facilities to record and link findings and evidence

Visual Analytics as Interactive Processes

Essential interactive components:

- Visual and textual query mechanisms,
- Annotation of visualization,
- Representation of findings and their relation, e.g. strong correlation between body weight and blood pressure, between age and blood pressure and between blood pressure and heart disease
  - Provide knowledge views or diagrammatic representations (concept maps, mind maps) or timelines (Shrinivasan, 2008)
- Enable to share and reuse analysis workflows
- Automatically record navigation steps

Visual Analytics as Interactive Processes

A few remarks on recording evidence (Shrinivasan, 2008):

- Knowledge construction is an unsystematic, evolving process
- Keeping track of findings and recording them externally is essential and should be easily possible at all times.
- History trees support tracking of exploration and navigation.

Various systems provide advanced features for recording findings and evidence.

Often, only final results are recorded; not the essential intermediate steps to achieve them.

Modes of human-computer interaction in VA:

- **Relevance feedback**: The system presents views, e.g. scatterplots, parallel coordinates, and user assesses them as interesting or relevant. The system records these decisions and learns from them to make suggestions in later analytic sessions (Behrisch, 2014).
- **Intelligent queries**: Instead of simple data base queries, queries by example or sketch-based queries (data like this). (Hao, 2007)

Some modes are derived from information retrieval.

Visual Analytics as Interactive Processes

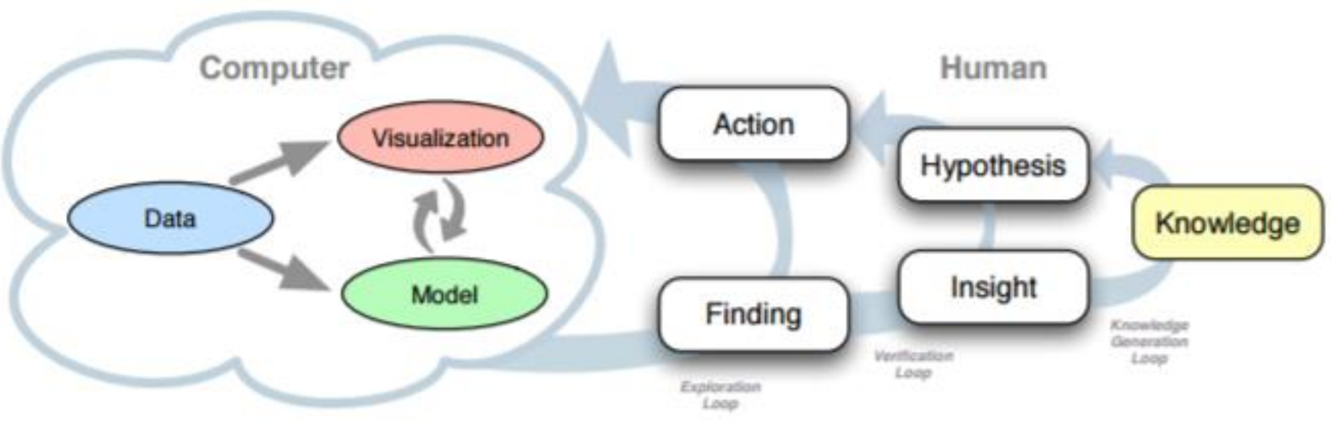
Essential terms (from Sacha, 2014):

- *Finding*. An interesting observation made by an analyst, e.g. missing values, an outlier, a certain data property, …
  - independent from the problem domain, but interpreted w.r.t. the domain often leading to further interaction.
- *Insight*. A unit of discovery. Complex, deep, unexpected and relevant (Saraiya, 2006, North, 2006).

– related to the problem domain, e.g. an unexpected relation.

- Hypothesis. An assumption about the problem domain that is subject to analysis (analysts try to find evidence supporting or contradicting the hypothesis.
- (Trusted) Knowledge. Insights lead to actions to verify them, trying to find very convincing evidence, e.g. high statistical significance, exploration on new data. → Justified belief (Bertini, 2009)

Visual Analytics as Interactive Processes



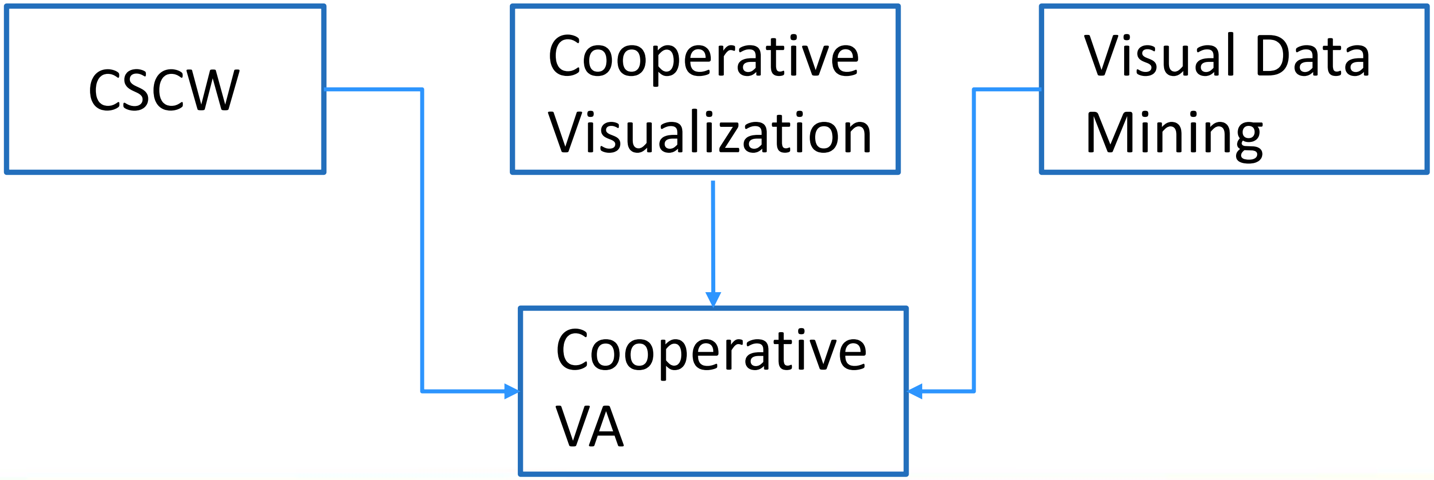
The relation between findings, insights, knowledge and hypothesis in the exploration loop, verification loop and knowledge generation loop (From: Sacha, 2014).

Cooperative Visual Analytics

So far, we discussed ***cognitive tools*** to enhance the analysis of data: visualization integrated with analytical tools.

Cooperative VA emphasizes ***social tools*** to enable and improve communication in the analytical reasoning (incl. traditional cognitive VA tools)

Coop. Vis. (Pang, 1997, Wood, 1998) provides remote rendering, methods to reduce network traffic, …



Cooperative Visual Analytics

Motivation:

- Increasing size and complexity of datasets, streaming data and related (research) questions
- Increasing specialization in professional life (often only one team member is specialized on a specific task)

→ single users are not able to fully exploit datasets, to answer all questions

→ shared visual representations, discussions of data, analytic results and interpretation improves understanding

→ explicitly support the needs of multiple cooperating analysts (Brennan, 2006)

Cooperative Visual Analytics

„It is when all our analysts get together and work out the differences and challenge each other with facts that we a get a better and more prominent answer.“ (Chin, 2009)

Technical development:

- Display sizes are increasing; prices decreasing
- Tabletop displays enable multitouch input

→ favorable for collaborative VA

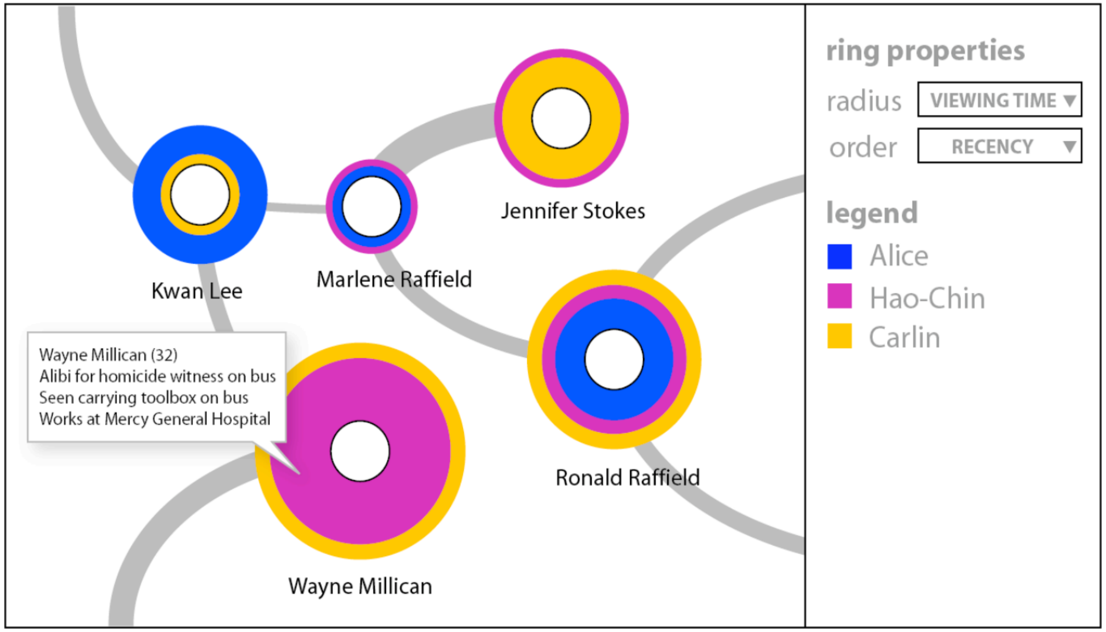
Goals:

- Support multiple analysts in
  - reasoning about uncertain data (Brennan, 2006)
  - reaching consensus in interpreting data
  - forming and testing hypothesis

Essential aspects of cooperative work:

- Awareness for group members and their activities
- Group dynamics, sometimes moderation, sometimes an instructor sets a starting point (Wood, 1998)
- „Common ground“ is essential, shared assumptions, attitudes, artifacts. → Externalisation on a display
- Motivational aspects, primarily intrinsic, strengthened by (positive) feedback
  – Trust and reputation (may be increased)
- Effectiveness depends on group size; from a certain limit effectiveness is reduced
- Group diversity influences effectiveness.

How to support awareness?



Visualizations that indicate who analyzed what how long and how recently. Example from intelligence analysis; colors indicate analyst (From: Balakrishnan, 2010).

Cooperative Visual Analytics

Further aspects (Heer, 2008, VA):

- Cooperation involves division of labor to participants
- Allocation of tasks according to skill sets
- Integration of results (involving a cost)
  - Quality control
  - Aggregation to more high level results

Model of visual analytics:

Consider two major stages of analytic activities (Pirolli, 1999):

- Information gathering (foraging loop)
- Sensemaking

Stages are not completely disjunct. Cycling activities may involve gathering and sense-making.

Gathering may involve to derive data (aggregated information, gradients, …) and sense-making involves data reduction, filtering, analytic activities, forming connections and hypothesis.

Cooperative Visual Analytics

- Cooperation involves
  - communication,
  - joint use of an analytic system,
  - joint creation of analytical artifacts
- System use involves
  - Uploading, cleaning, preparing data
  - queries (define search terms),
  - navigation in results,
  - use of analytic techniques,
  - exploration of results
- Artifacts involve
  - concept maps,
  - presentations

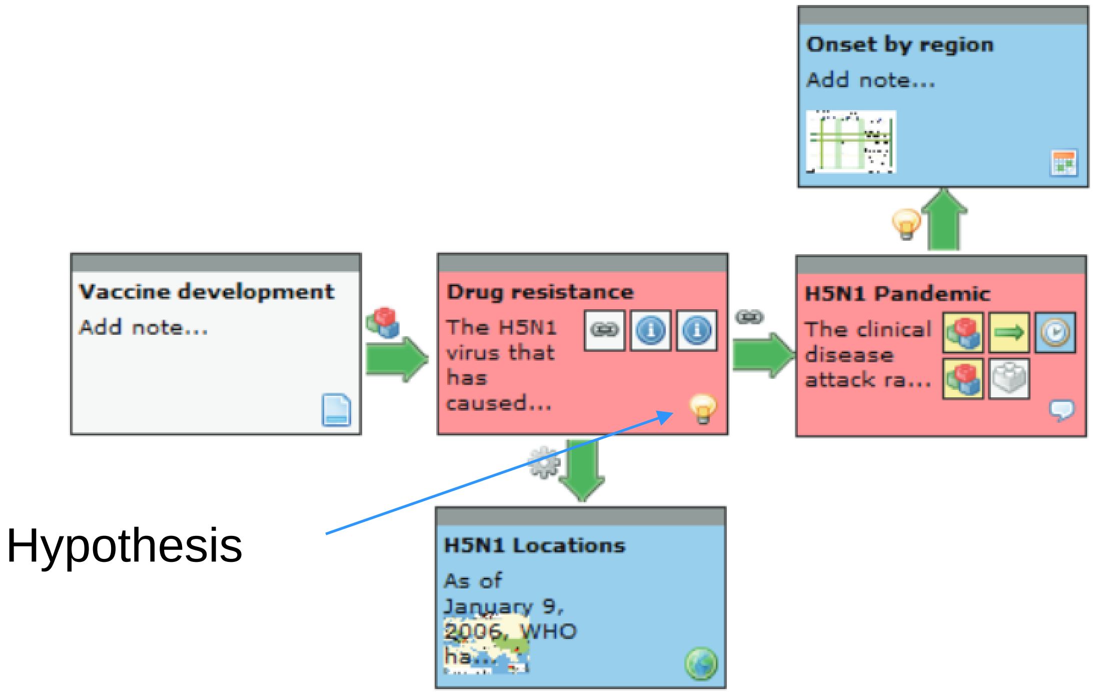
Cooperative Visual Analytics

Visual Analytics tools often provide support for:

- Gathering information,
- Organizing information, e.g. setting bookmarks
- Explore information,
- Record findings

Scalabe visual reasoning (Pike, 2007):

- Graphical workflow mechanism for recording evidence, assumptions, arguments, hypothesis and other reasoning structures
- Assumptions reveal mental models and cognitive biases (Kahnemann, 2011), arguments and linked assumptions, hypothesis combine arguments and assumptions.



Analytic pathway for an avian flu analysis (From: Pike, 2007). Concept maps contain arrows and icons representing assumptions, hypothesis, etc. They may be opened and reveal a (deep) substructure. Assumptions, evidence and hypothesis are connected with **confidence** (from strong in favor to strong against).

Cooperative Visual Analytics

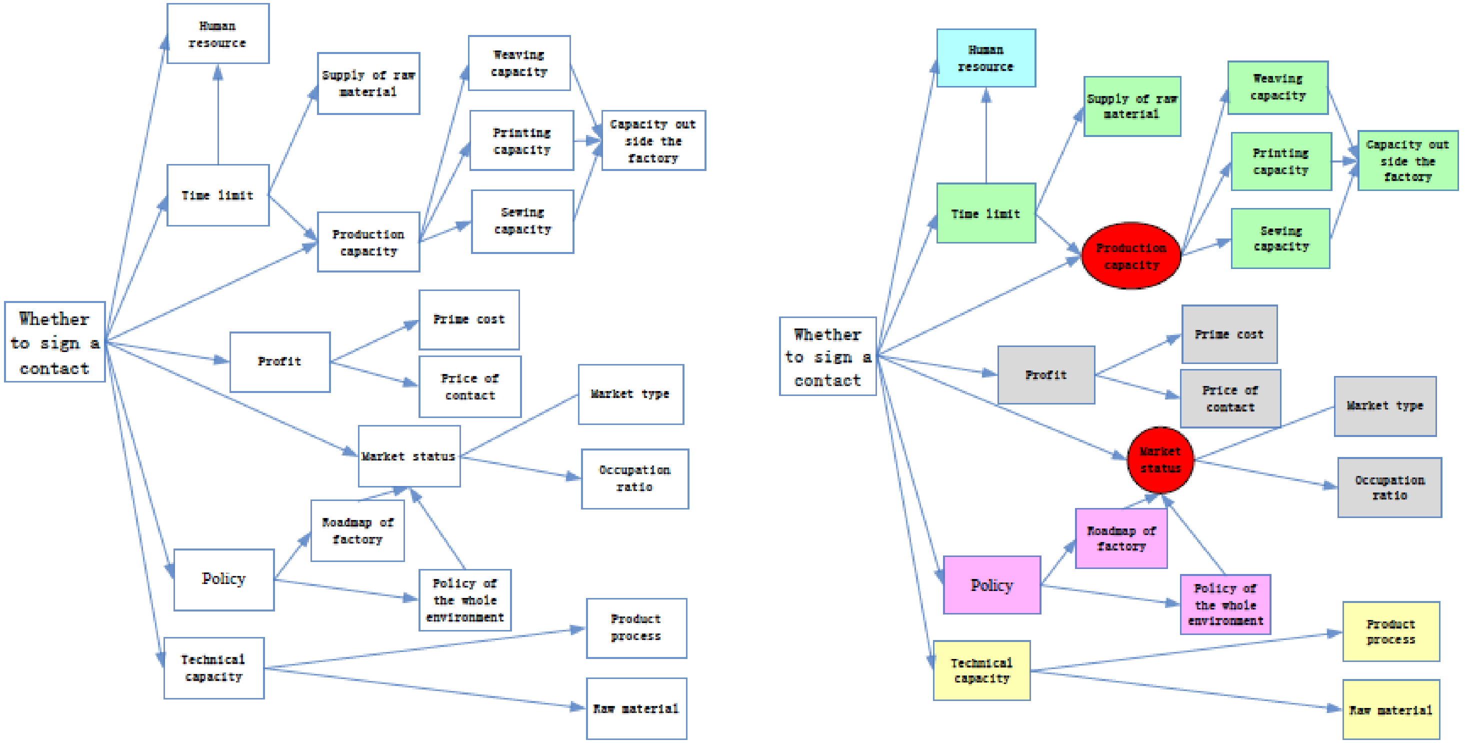
A few remarks on concept maps:

- Node-edge representation for representing knowledge (Novak, 1990; invented by him in the 1970s).
- (Labeled) Edges indicate links/relations between concepts *(linking words)*
- Cross links between distant nodes are possible.
- May be linked to images and videos
- Often hierarchical with the top level concept displayed on top or very left
- Similar to but more formalized than mind maps

Visual analytics tools, e.g. in intelligence analysis, support concept maps.

Cooperative tools indicate who created which part.

Cooperative Visual Analytics



Single user and collaborative concept map. Color and shape indicate whether only the current user created a node (gray) or multiple users. A sketch-based interface supporting the creation, modification, deletion and undo supports cooperative construction (From: Du, 2011).

Table 1. Mapping between gesture and operation.

Gesture					
Operation	Undo	Redo	Delete (node or edge)	Create node	Edit (node or edge)

Gestures for a sketch-based interface to collaboratively create a concept map (From: Du, 2011).

Subviews of selected portions of the concept map, overview visualizations and zooming are essential.

Co-Located Visual Analytics: Displays

Displays and devices (Heer, 2008, InfoVis):

- Systems supporting multiple analysts benefit from more display space or the use of multiple displays
- Cooperative VA often employ
  - table top displays, e.g. 70 ‘ ‘ diagonal, 4HD resolution
  - wall-sized display, or
  - a joint large display (shared view) along with mobile devices for each user (private views)
- Wall-sized displays often have low resolution (legibility of labels) and selection is challenging (laser pointer often a metaphor for selection)
- Each analyst should have one device to control the shared view → parallel processing

Co-Located Visual Analytics: Displays

Multiple display environments (MDEs), (Waldner, 2009):

- enable a natural combination of private and shared views,
- should be flexible enough to integrate private devices (bring your own device)
- require special consideration for techniques such as brushing and linking as well as dragging (from display to display)

Size, display angle of shared displays influence legibility of content.

Co-Located Visual Analytics: Displays

Courtesy of ICCAS Leipzig

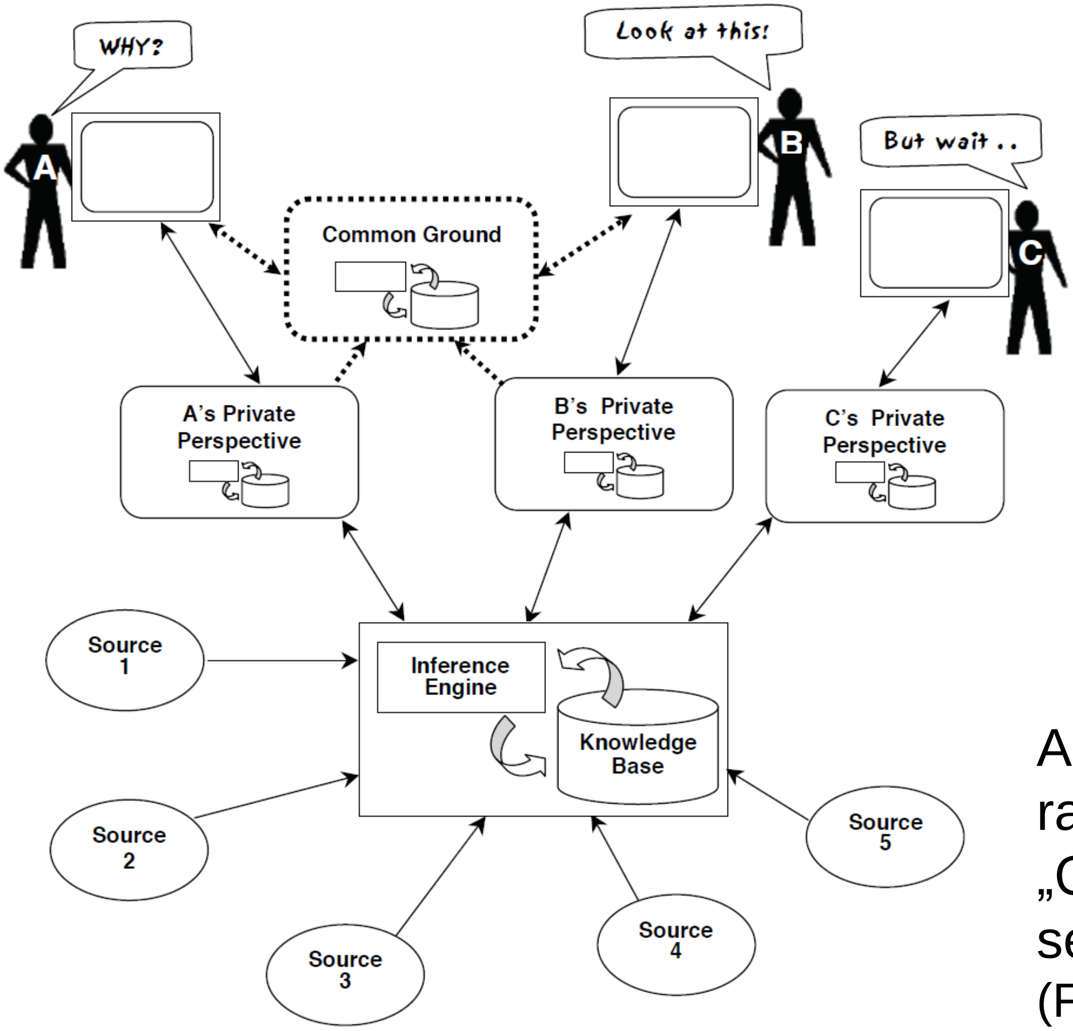
Medical doctors have access to patient and image data on their laptops and have a large (40ʻʻ display) for a shared view and joint discussion of treatment planning.

Co-Located Visual Analytics

Data processing:

- Visualization and analysis of large data sets is challenging w.r.t. efficiency
- To support cooperation, data needs to be updated in different private and shared views → increased computational effort, very efficient processing needed, e.g. with bricking, parallel computing, hierarchical data structures
- Fluidity is even more essential in collaborative settings (Heer, 2008, InfoVis)

Co-Located Visual Analytics



Architecture for a Collaborative VA system. The „Common Ground" represents the shared view (From: Brennan, 2006).

Co-Located Visual Analytics

- Employs natural human experience of cooperation
- Subtle signs are inconciously used to trigger or stop activities in a socially accepted manner

Requirements:

- Design of interactive systems requires an understanding of this (inconcisous) behavior
- Cooperation involves private and shared spaces and facilities to share private data/views/analysis results
- Sources and reliability of data needs to be considered (Brennan, 2006)
- Sharing information should be as easy as possible

Co-Located Visual Analytics: Note-Taking

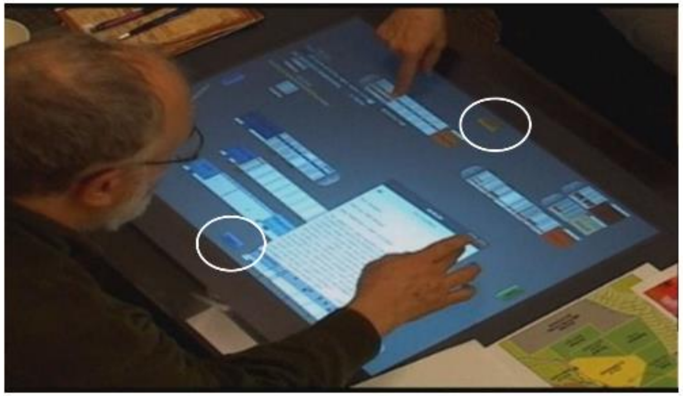
Note-taking is an essential activity taking considerable time in experiments and real-world settings (Mayhar, 2013).

- Involves writing, annotation (arrows, encircling) and saving charts and other visual representations
- Pen-based input on mobile devices as preferable interaction style
- Teams differ strongly in which type of note-taking is prevailing

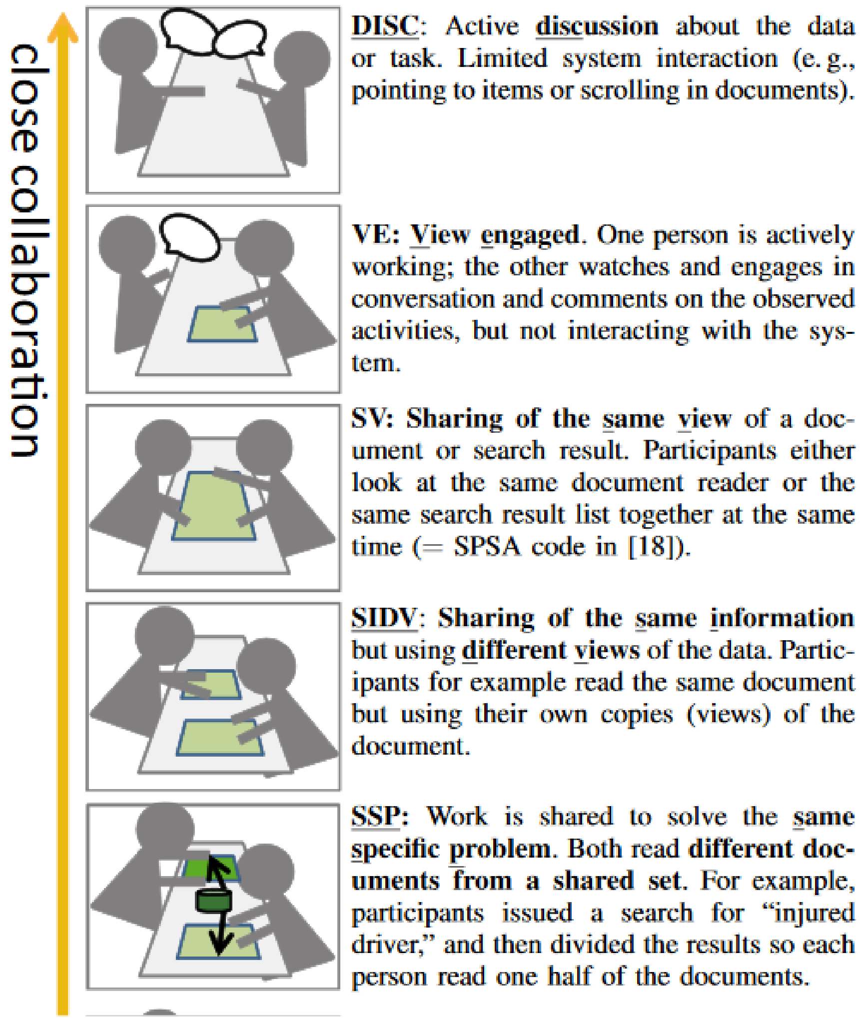
Co-Located Visual Analytics: Case Study (I)

Small teams (pairs) using one large digital table to explore text document collections and solve a problem (Isenberg, 2012)

Analysts search for data, pull a document on the desktop, zoom in for reading and display and share on a tabletop display (Microsoft surface).



Each analyst has a separate „search button“. Teams may work independently and jointly.



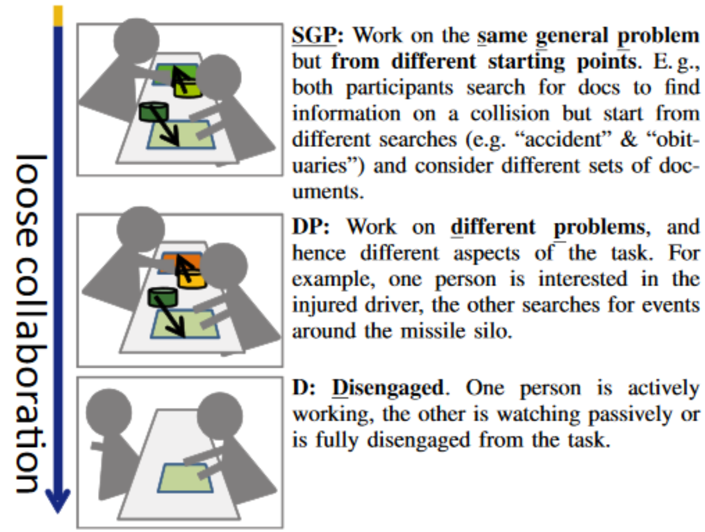
DISC: Active **discussion** about the data or task. Limited system interaction (e. g., pointing to items or scrolling in documents).

VE: View engaged. One person is actively working; the other watches and engages in conversation and comments on the observed activities, but not interacting with the system.

SV: Sharing of the same view of a document or search result. Participants either look at the same document reader or the same search result list together at the same time (= SPSA code in [18]).

SIDV: **Sharing of the same information** but using **different views** of the data. Participants for example read the same document but using their own copies (views) of the document.

SSP: Work is shared to solve the same specific problem. Both read **different documents from a shared set**. For example, participants issued a search for "injured driver," and then divided the results so each person read one half of the documents.



SGP: Work on the same general problem but from different starting points. E. g., both participants search for docs to find information on a collision but start from different searches (e.g. "accident" & "obituaries") and consider different sets of documents.

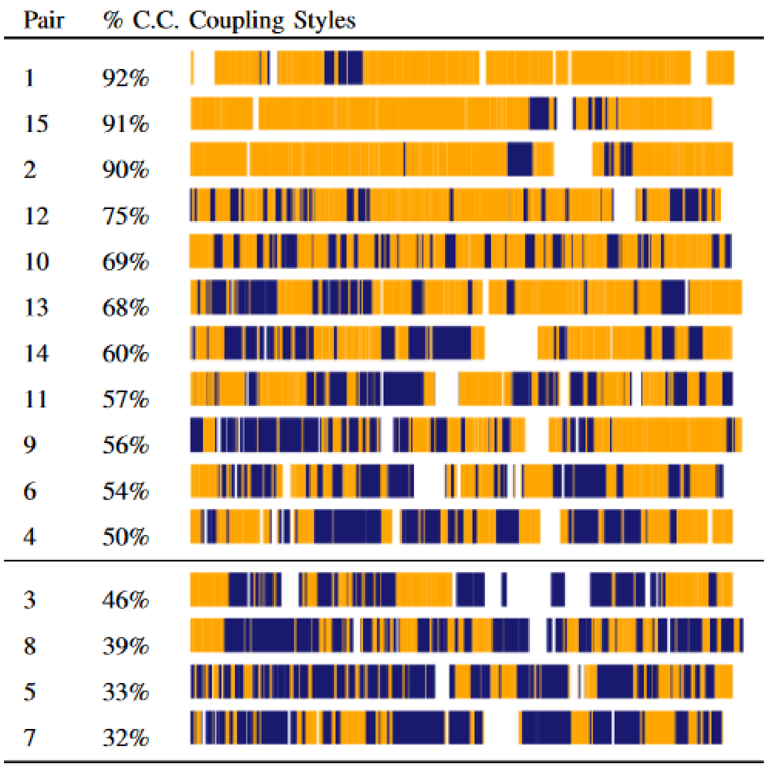
DP: Work on different problems, and hence different aspects of the task. For example, one person is interested in the injured driver, the other searches for events around the missile silo.

D: Disengaged. One person is actively working, the other is watching passively or is fully disengaged from the task.

Styles of cooperation. The intensity differs strongly in loose and close collaboration

(From: Isenberg, 2012)

Co-Located Visual Analytics: Case Study (I)



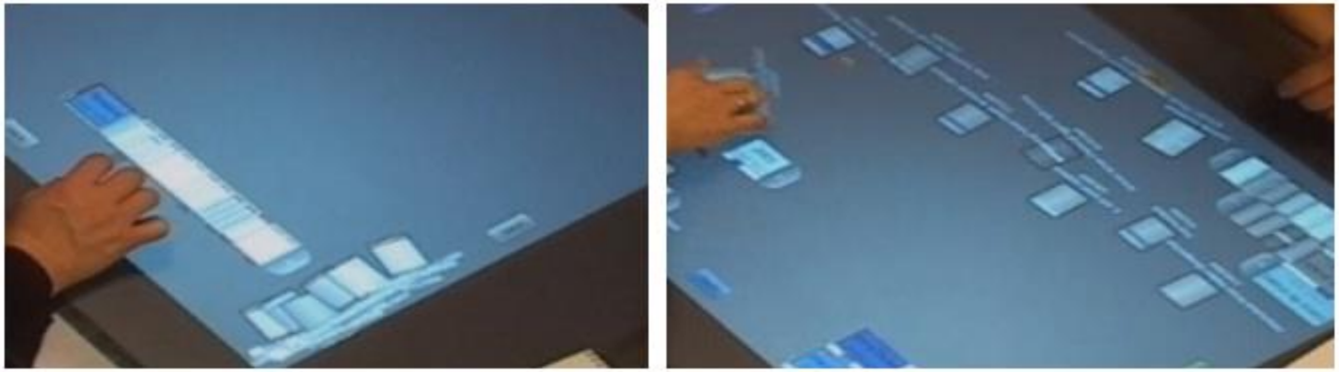
15 pairs were observed. They differ in the amount of close cooperation (between 32 and 92 %)
(From: Isenberg, 2012).

Pairs that cooperated more closely were (on average) more successful.

Co-Located Visual Analytics: Case Study (I)

Workspace Organization:

- Early stages: Information is collected and just dragged to the information space
- Later stages: Users clean up, order and categorize, e.g. along a time line or common topics



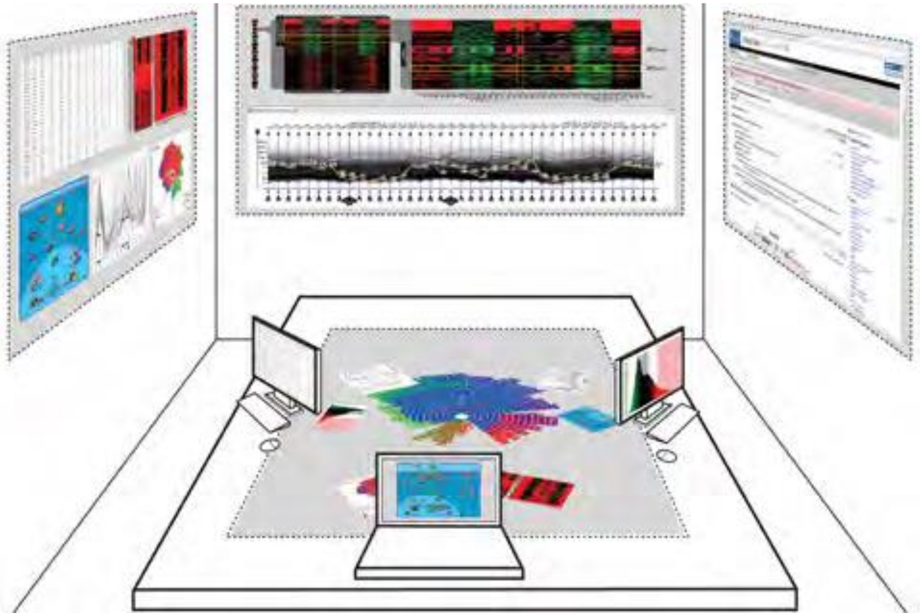
Organization of documents according to importance (left) and along a timeline (right).

Co-Located Visual Analytics: Case Study (II)

Multi-level cooperative visual analytics (Streit, 2009).

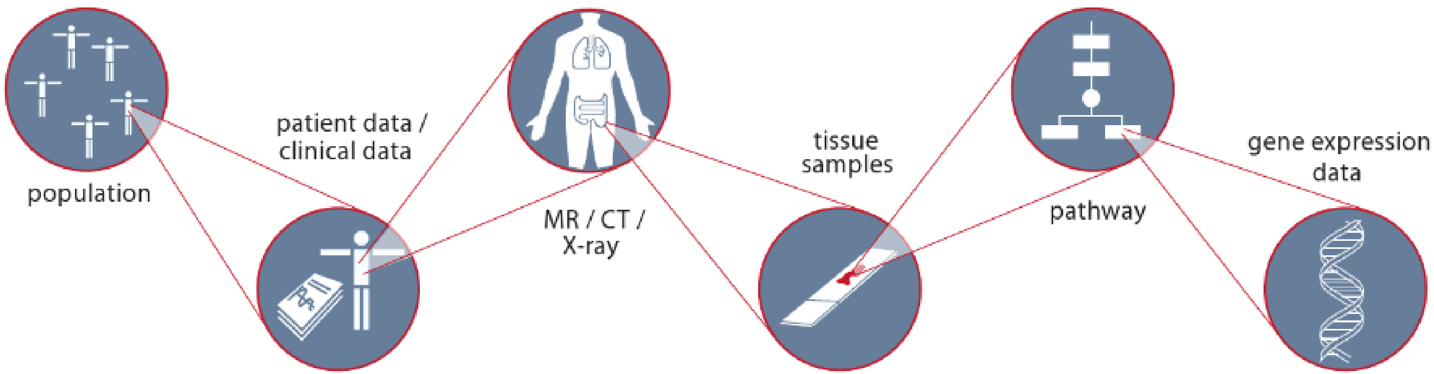
Scenario: for tumor treatment planning experts and data are integrated and considered for decision making.

- **Oncologists** providing CT/MR scans and treatment history
- **Pathologist** providing tissue samples (from biopsy)
- **Geneticist** providing gene sequence data

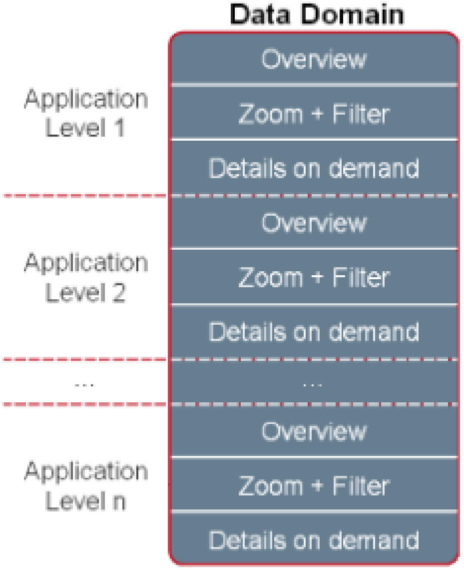


Multi-display environment with shared and private displays (Streit, 2009)

Co-Located Visual Analytics: Case Study (II)



Data at different levels need to be integrated. For all levels overview, zoom and filter and details on demand are provided (From: Streit, 2009)



Co-Located Visual Analytics: Case Study (II)

Key features:

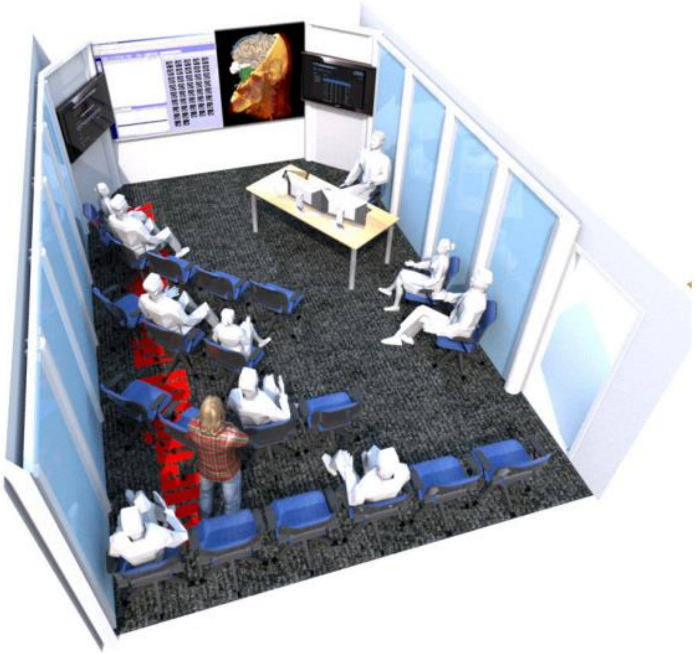
The visualization level of detail is

- Adapted to display size
- Is adjustable for the user

Visual linking supports emphasis (lines drawn between related elements at different views).

Built on a flexible framework (Deskotheque, Waldner, 2009) that acquires a model of the 3D space and adapts geometric compensation and edge blending.

Co-Located Visual Analytics: Case Study (II)



A similar development: tumorboard.

The new tumorboard (right) with more large displays and personal displays enables collaborative decisions. A voting system is installed. (Stefan Bohn, ICCAS Leipzig) (see also Meier, 2015)

Co-Located Visual Analytics: Summary

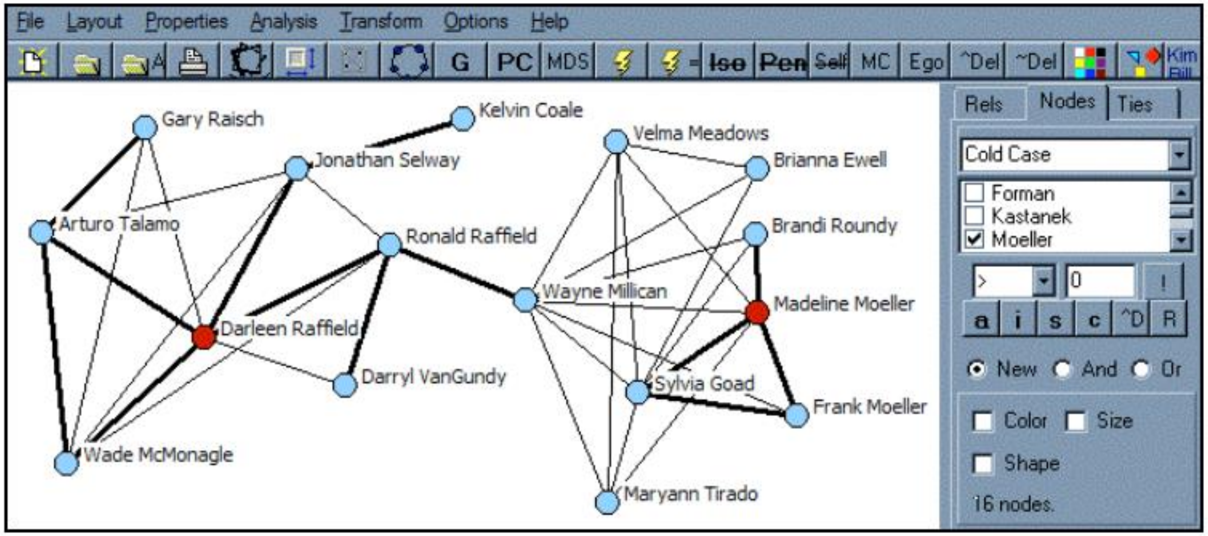
Essential Aspects:

- Shared spaces for close cooperation and private spaces for stages of individual analytic activities
- Easy sharing of data and annotations
- Support for note-taking

Distributed (Remote) Visual Analytics

- Analysts cooperate in a synchronized manner but are not face to face.
- Video-conference, team viewer or similar techniques are employed.
- Easy sharing of screen content is essential.
- Interesting question what should be shared for optimal efficiency.
  - For intelligence analysis: should each analyst have access to all (overwhelming) information or to a part of the data only where arguments/hypothesis are shared resulting from the remaining data.
  - Study of (Balakrishnan, 2010) indicates that sharing arguments leads to better results. Analysts explored more options (larger diversity is fostered).

Visualizations to support VA in intelligence analysis



NetDraw visualization with suspicious persons and their major contacts (From: Balakrishnan, 2010).

When each analyst is responsible for analyzing parts of the data herself, she has a sense of *ownership* which is favorable.

Asynchronous Cooperation

Asynchronous VA (Heer, 2007)

- does not benefit from the group dynamics of a joint activity
- Benefits from the freedom in space and time

Essential success stories of asynchronous cooperation involve Wikipedia, Wikimapia, Cycling path Wiki, online discussion, open source software, social media, ManyEyes (Viegas, 2007)

Essential elements:

- Annotation, commenting (start new or add thread), adding new content, assessment, chat (for switching to synchr. mode, e.g. in ManyEyes)
- Design supports motivation (contributions clearly visible)

Asynchronous Cooperation

- Voyagers and Voyeurs: Supporting Asynchronous Collaborative Information Visualization
- CommentSpace: structured support for collaborative visual analysis
- Combining synchronous and asynchronous collaboration within 3D city models, (Döllner, 2010)
- History tools for collaborative visualization, (Tory, 2009)
- Supporting awareness through collaborative brushing and linking of tabular data (Mahyar, 2013)

Pair and Group Analytics

Pair analytics (Arias, 2011):

- Strategy inspired by pair programming: one expert explains a solution to another and by verbalizing and discussing shortcomings, alternatives and improvements are discovered.
- Involves a domain expert, e.g. a security or finance expert, and a computer science expert and intensive communication on the intent of the domain expert and the analytics techniques to fulfil this intent.
- May be realized as co-located or remote cooperation (Balakrishnan, 2010; Klemm, 2016).

Pair and Group Analytics

Benefits:

- by cooperating, both experts naturally discuss (*think aloud*) and improve their mutual understanding
- by analyzing the discussion, many insights for further developing the analyticsl system can be expected.
- Face-to-face communication in co-located pair analytics is natural and effective.

Group analytics:

- Extension of pair analytics to multiple (a few) domain experts. Complex research questions, e.g. in public health benefit from the different perspectives.

Pair and Group Analytics

Co-located Pair analytics in a health care application: Specialists for injury prevention cooperate with a computer science specialist to analyze injury data

(From: Al-Hajj, 2013).

Evaluation

- Many systems, visualization, interaction and analysis techniques have been developed.
  - Systematic analysis and comparison is needed.
- Design choices often based on guidelines for presenting (time-oriented) data and interaction principles.
- Despite this basis, it needs to be carefully tested whether systems indeed support physicians and clinical researchers.
- Evaluation aims at understanding
  - How the system is actually used
  - How usable the system is
  - How the system contributes to patient care or medical research

Evaluation

Methods of evaluation:

- Task-based experiments
  - In-depth analysis how target users explore and analyze predefined data
  - Document the decision-making process and conclusions
  - Do users trust the systems/data?
  - Major limitation: short term use of an unfamiliar system
- Usability analysis
  - Analyze log-protocols to understand
    - Which functions are used
    - How often
    - In which sequence/context
  - Record think-aloud comments (recall pair analytics) to understand why certain functions are involved.

Evaluation

Methods of evaluation (II):

- Insight-based evaluation for long-term use (North, 2006).
  - A few users use the system for an extended period of time (at least weeks).
  - They employ datasets and tasks relevant to them.
  - The reasoning process is carefully documented with a research diary including notes and annotated screenshots.
  - Explicitly record new insights, their relation and significance/implications
  - Analysis:
    - How are insights related to each other? Refinements? Complementary?
- Specific example: microarray experiments (noisy, complex bioinformatics data)

Evaluation

Methods of evaluation (III):

- Use contest data, e.g. from the VAST challenges comprising text analytics (based on a large set of text documents), movement tracking data of park visitors and compare how your users solved the problems in comparison with other system‘s use.

  → better understanding of strength and limitations, e.g. Isenberg, 2012 describing a collaborative system

Summary

- Analytic reasoning of complex data is naturally a cooperative process
- Different analysts, including visual analytics and subject matter experts may contribute with different perspectives (pair and group analytics)
- Social aspects, established forms of communication and cooperation, group dynamics need to be considered.
- Successful examples range co-located to remote and asynchronous cooperation supported by appropriate devices (display, input) and interaction techniques.

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