Visual Analytics in Healthcare

Introduction

„Interactive information visualization and visual analytics methods will bring profound changes to personal health programs, clinical healthcare delivery, and public health policy making.“

→ target user groups: clinicians, medical researchers, health care policy makers and patients

„The challenges are aligned with the National Institute of Health‘s roadmap for Predictive, Preemptive, Personalized and Participative Medicine.“ (Shneiderman, 2013)

„Medical care, in particular for chronic diseases, accumulates a huge amount of patient data over extensive time periods.“ (Rind, 2013)

Introduction

Three domains for Health 2.0 are defined (Hesse, 2010):

1. **Personal Health Information**: individual collect information related to their health using sensors, etc.

2. **Clinical Health Information**: Electronic Health Re-cords (EHR) comprise comprehensive information on patient care. EHRs may be used for decision making and clinical research. (openEHR: vendor-independent, person-centred EHR, see Link)

3. **Public Health Information**: State governments collect large amounts of public health data to support health policy w.r.t. preventive measures, e.g. cancer screening

Domains partially overlap. Focus on (2.). Target users are professionals that make rapid decisions in distracting environments. Few examples for (1.) and (3.)

Introduction

Patient data: *high dimensional description of patient conditions*, involving diagnosis and treatment, measurements of various conditions (derived from blood samples, urin samples).

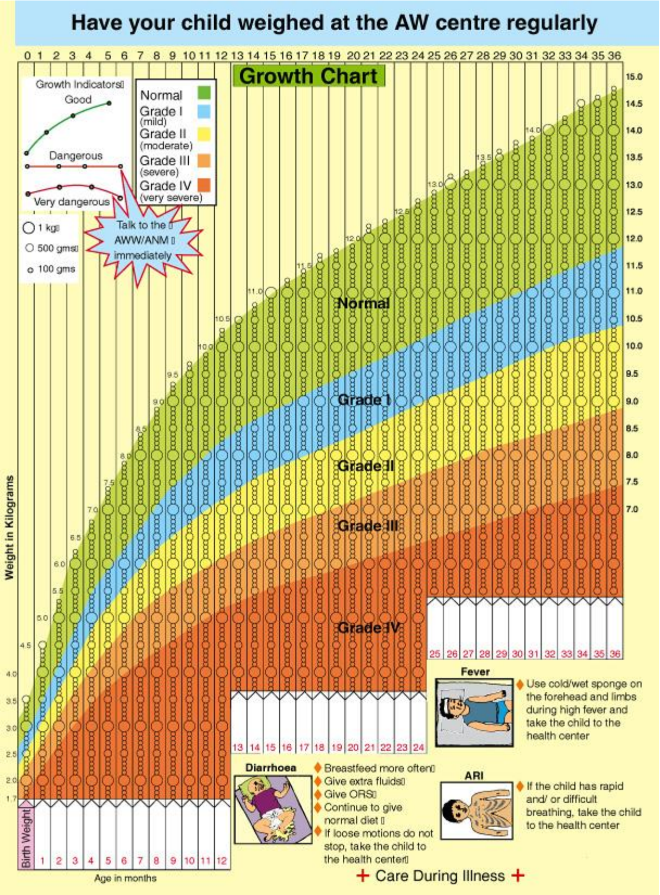
Patient data is *inherently time-dependent* and often analyzed to understand how previous treatment decisons affected the patients‘ state (on a scale of weeks/months).

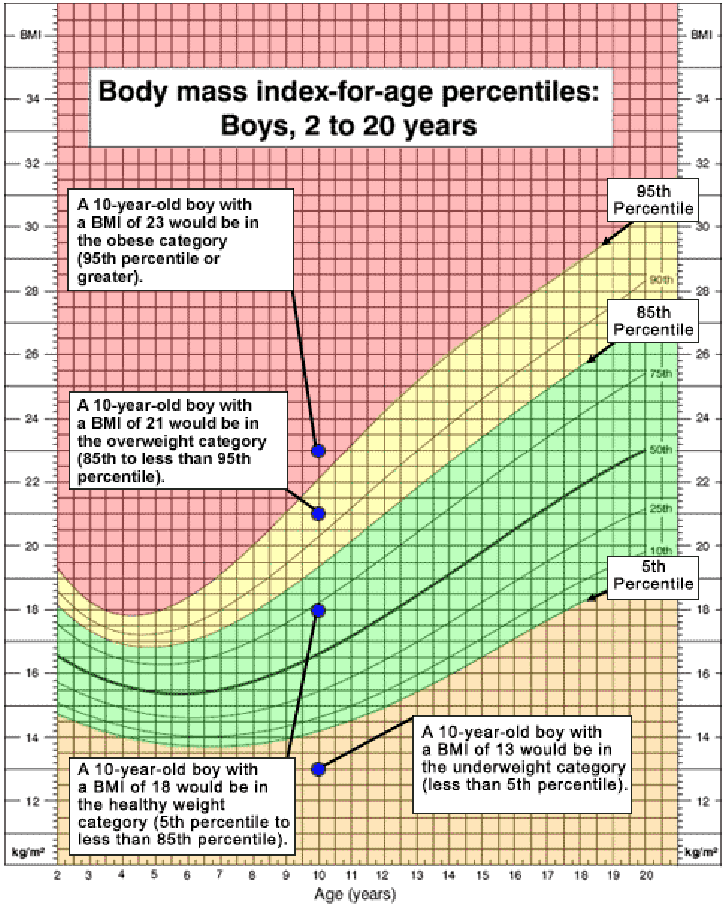
Cohort study data involves *answers to questionaires*, e.g. about drinking and smoking habits, nutrition, physical activities, income, employment, …

Members of a cohort *are chosen randomly* to achieve a represen-tative sample of the population (w.r.t. age, gender, social status).

Cohort study data is more static (five years between the cycles) and is analyzed for understanding *risk and protection factors*.

Introduction





Visualization for preventive medicine. Normal and abnormal ranges of weight and BMI w.r.t. sex and age.

(From: Link$_1$ and Link$_2$)

Introduction

- Patient and cohort study data comprise numerical values (Body mass index, age, blood pressure, …) and categorical often binary values (married?, previous cancer diagnosis?, smoker?)
- Different patient data is comparable to a certain extent only.
  - Different nurses and physicians perform measurements slightly differently. MR and CT scanners differ.
- Cohort study data is comparable to a larger extent since the whole data acquisition aims for ideal comparability.
  - Self-reported data (e.g. about drinking, smoking, use of drugs, sexual activities, …) however, is not reliable.

Introduction

„Within such (patient) data, relevant and interesting structural or temporal patterns („knowledge“) are often hidden and not accessible to domain experts. The concepts of „relevant“ and „interesting“ … are not crisply defined and inherently dependent on context and subjective judgement … “ (Hund, 2015)

Introduction

Challenges for Visual Analytics Solutions:

- Offering timely information in the right format
- Facilitate team decision making
- Characterizing and understanding similarity
- Visualizing comparative effectiveness and cause-effect relationships
- Presenting risk and uncertainty
- Evaluation under real-life situations (troubled patients, overloaded physicians, …)

(Adapted from Shneiderman, 2013)

VA in health care involves sensible health data.

Thus, the following is essential:

- Data is often processed in anonymized form.
  - Exception: Individual decision making for a patient
- Special care is necessary if rare features or diseases in combination allow to identify a person

Outline

- Decision Support for Clinical Treatment: Single Patients
  - Visual Analysis of Patient Data over Time
  - Decision support by analyzing „similar" patients
- Visual Exploration of Multiple Patients
- Visual Analytics of Cohort Study Data
  - Hypotheses-based workflows in Epidemiology
  - Hypothesis generation with Visual Analytics
  - Cohort construction and comparison
- Identification of adverse drug effects
  - Co-occurence of drugs and adverse reaction
  - Emphasis on severe effects of low frequency
- Visual Analytics for Public Health
  - Epidemic modeling, prevention of injuries, nutrition behavior
- Patient Information and Comparison

Decision Support for Clinical Treatment

„Physicians are confronted with increasingly complex patient histories based on which they must make life-critical decisions. … Clinical researchers are eager to study the growing databases of patient histories to detect unknown patterns, ensure quality control and discover surprising outcomes.“ (Rind, 2013)

„The increasing data in EHRs challenge the physicians capacity to grasp an overview of the patient history while seeing specific data that alert them to potential problems.“ (Shneiderman, 2013)

→ Target user groups: physicians and researchers

Decision Support for Clinical Treatment

Decision-making based on patient status, symptoms, medical history, past and ongoing treatments.

Data

- is increasingly available electronically (Electronic Health Record, EHR).
- is often distributed over various databases, leading to challenging schema mapping and integration problems

EHRs are primarily used for billing and legal reasons.

To improve clinical care, tailored user interfaces and visualizations are essential.

Current practice: often textual, many tables and screens, query languages such as medical SQL variants

Decision Support for Clinical Treatment

Exploration of EHR or hospital stay data related to the following questions:

- What are typical sequences of diagnosis, medication and treatment related to a particular disease?
- How do these sequences relate to an outcome?
- How often do sequences deviate from clinical guidelines?
- What are typical deviations? And how they relate to the outcome?
- Do unusual sequences occur? E.g. patient transferred from ICU, to normal room and soon back to ICU?

Decision Support for Clinical Treatment

Electronic Medical/Health Records (EHR, EMR):

- Data structure driven by administrative, regulatory, financial and legal needs.
- Since the 1960s, records were used for treatment planning
- Involves different data types, e.g. laboratory values (numerical), scores summarizing tests (ordinal, e.g. low, medium, high cholesterol), symptoms (subjective) and diagnosis (categorical or binary)
- Needs to be available in a highly *standardized manner* to enable efficient analysis.
  - Consistent use of terms.
  - Diseases specified according to ICD 10. (*International Statistical Classification of Diseases and Related Health Problems) (Link1, Link2)*

Decision Support for Clinical Treatment

Relation to Visual Analytics:

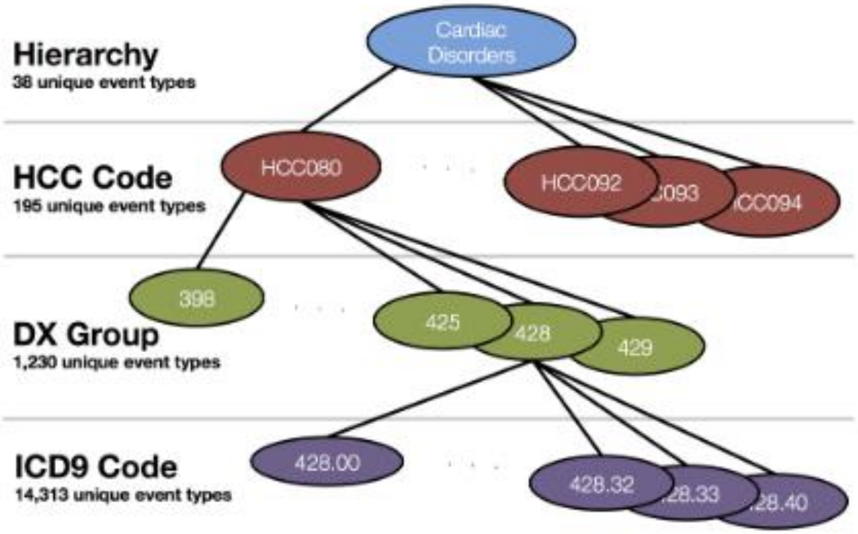
- Relevant data includes
  - Various point and interval events, e.g. treatment decisions
  - Other time-oriented data, being quantitative (blood pressure, glucose level, …) or categorical (diagnosis)
- Relevant visualization techniques include
  - Visualization of event-typed data
  - Visualization of other time-oriented data
  - Multidimensional visualization, e.g. glyphs
  - For some public health problems: spatio-temporal visualization, e.g. spread of infectious diseases

Representation of diseases according to ICD 9:

Diseases are represented within four levels

- Hierarchical condition category (38)
- Diagnosis groups (195)
- Diagnosis (1230)
- ICD9 codes (> 14.000)

Hierarchy may be used for grouping events flexibly.



Hierarchy of diseases (From: Du, 2016).

Decision Support for Clinical Treatment

Treatment plans:

- In addition to the patient state, treatment plans are essential and need to be analyzed together.

Treatment plans:

- Have an *intent* (a description of which lab. values, symptoms should be changed)
- *Conditions* when they can be applied
- Terminal conditions when they should be stopped
- May be *hierarchical* (involve subplans)
- Are *temporal* (drug prescriptions, chemo therapy, … have a duration)
- Become more and more digital

Decision Support for Clinical Treatment

Requirements:

- A summary of patient state
- Visualization of treatment plans (along with patient state)
- Run-time support, e.g. monitoring, reminders to planned clinical actions
- Systems need to be easy to use BUT also flexible to be adjusted to different patients/diseases/analysis goals
- Support interaction, such as
  - opening of documents (written reports),
  - annotation (enable to add notes)
  - Undo and history management

Decision Support for Clinical Treatment

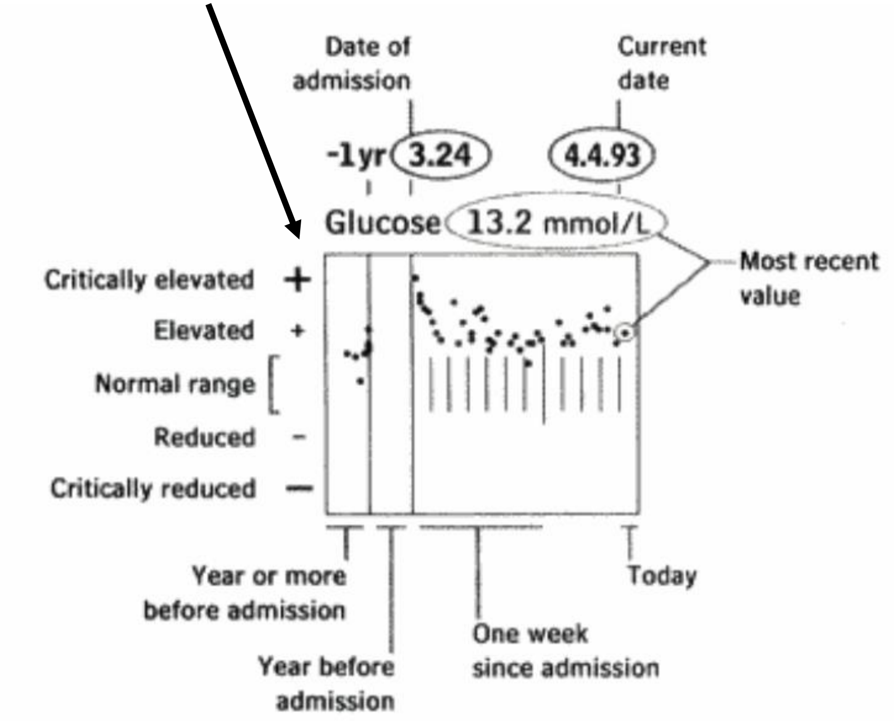
Systems for

- displaying development of quantitative values (Graphical Summary of Patient Status, MIVA, Midgaard)
- displaying event-typed data (LifeLines)
- combining visualization of quantitative and event-typed data (VisuExplore)
- Querying patient databases (Similan, LifeLines2)
- Displaying patient state and treatment plans (CareVis, CareCruiser)

Decision Support: Patient Summary

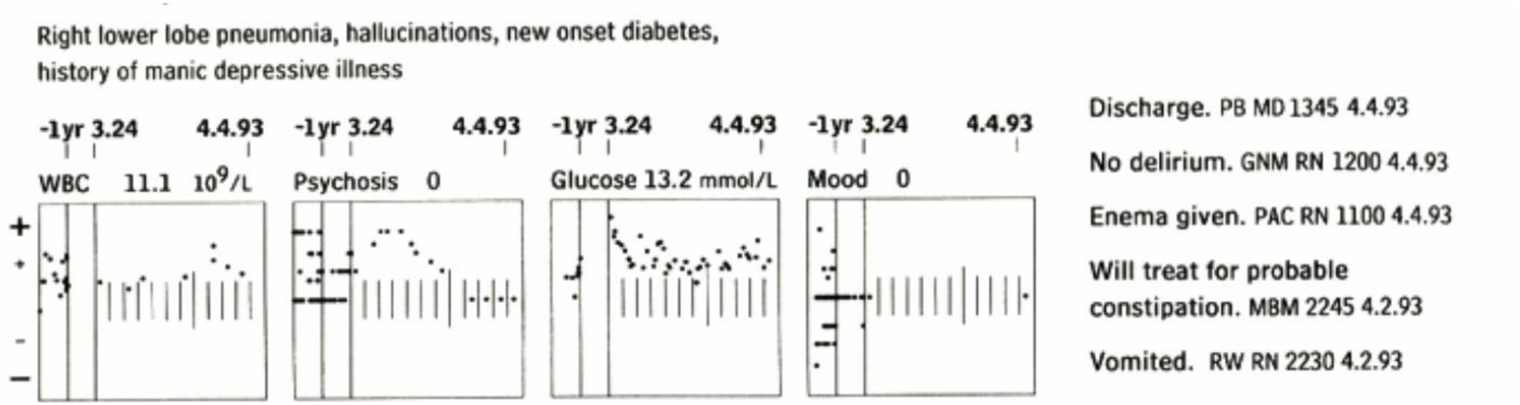
- Summary of patient state representing patient state compared to reference values/ recommended drug dose
- Such visualizations can be combined for different values. (Pownser, Tufte, 1994)
- Color could better emphasize critical values.
- Intended use: static visualizations for printing, not interactive exploration

Point plot



The time-scale is non-linear, focus is on recent time (Pownser, Tufte, 1994).

Decision Support: Patient Summary



Summary of different temporal developments added with manual notes, related to treatment. Major clinical problems on top.

InfoVis-concepts: Scatterplots, Small multiples

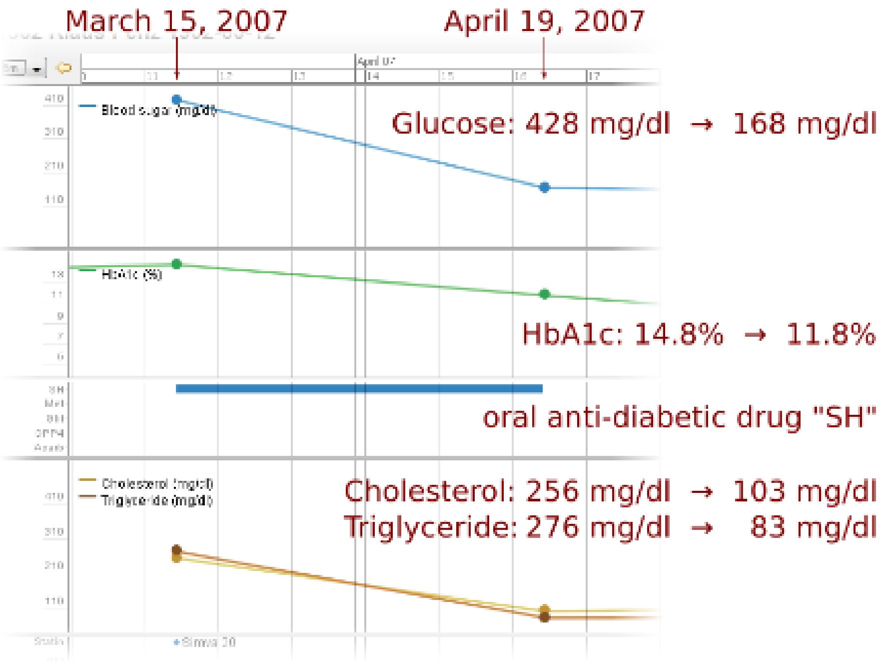
Further visualizations: scatterplots revealing drug dose and patient state correlations to optimize dosage.

Decision Support: Patient Summary

Enhanced patient summary with MIVA (Medical Information Visualization Assistant). Grey backgrounds represent range of normal values. The points on the right, very recent developments (Faiola, 2011).

Display of quantitative variables (From: Rind, 2011)

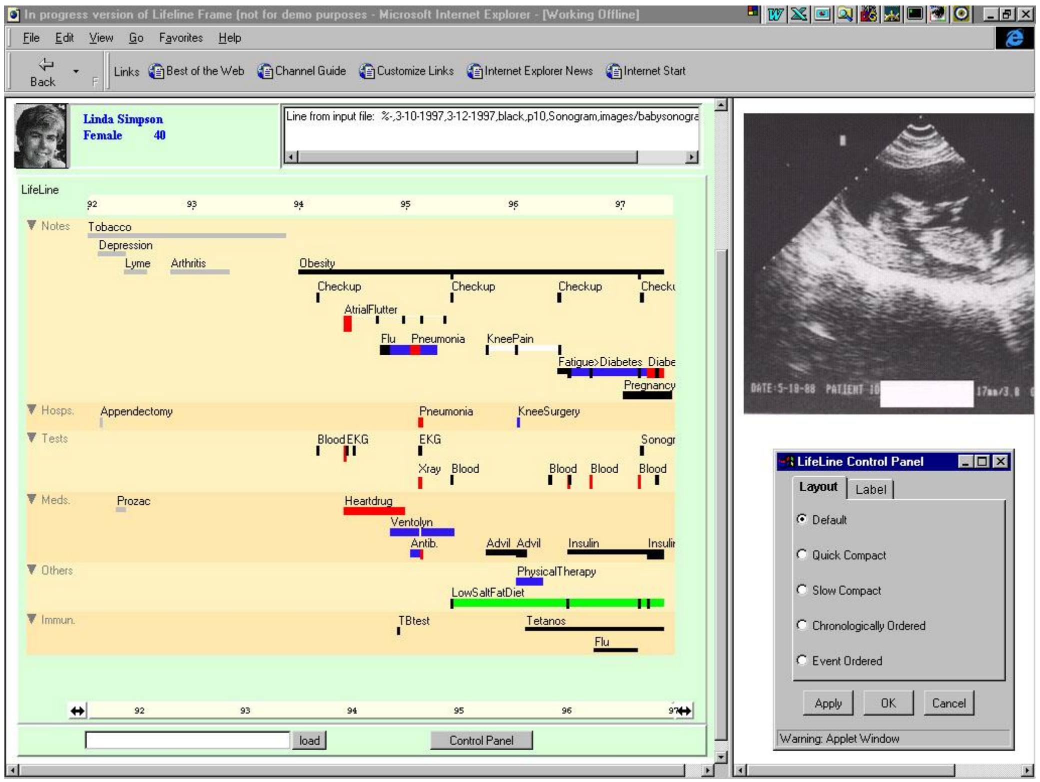
Labels are essential.



Decision Support for Clinical Treatment

LifeLines (Plaisant, 1998)

Explore **one** medical record with events and episodes. Color shows normal/abnormal states.



Basic Techniques

- Zoomable Timeline
- events grouped in facets
- Navigation
- Search e.g. for a symptom
- Tooltips and detailed views for selected events, e.g. ultrasound

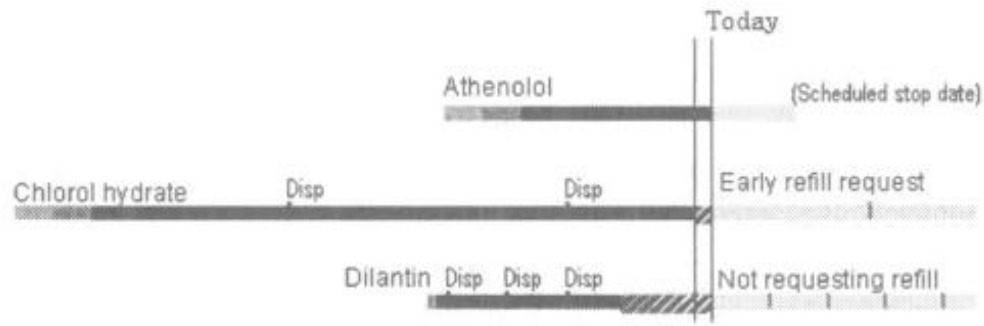
Decision Support for Clinical Treatment

Life Lines, advanced features

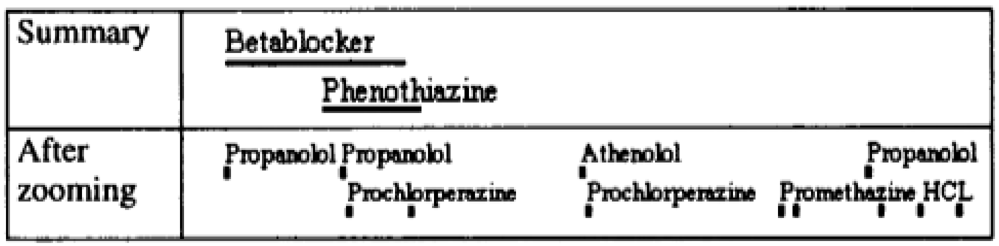
- Integration of interval events, e.g.
  - Drug prescriptions
  - Hospital stays
  - Diagnosis, such as depression, burn-out
- Event attributes
  - Severity of a disease
  - Cost (of diagnostic or therapeutic procedure)
  - Dosage
    - Mappings of such attributes to linewidth or linestyle
- Summary of events, e.g. similar consecutive events, such as prescription of the same/similar drug

Was also used for criminal and other personal „histories“

Decision Support for Clinical Treatment



LifeLines: Prescription of drugs and estimated duration for this drug. For the first drug, a stop date is entered to avoid overuse (From: Plaisant, 1998).



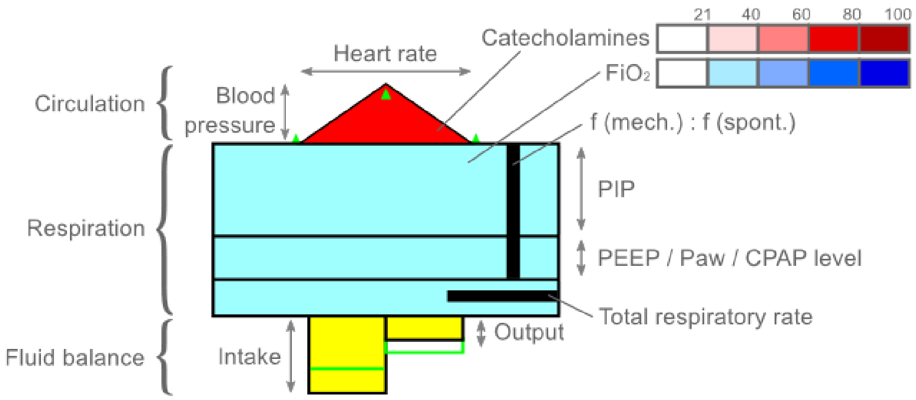
LifeLines: Summary of two drug classes (From: Plaisant, 1998).

Information is visualized in retrospect; LifeLines do not directly support planning.

Decision Support for Clinical Treatment

Glyph-based summary of patient state:

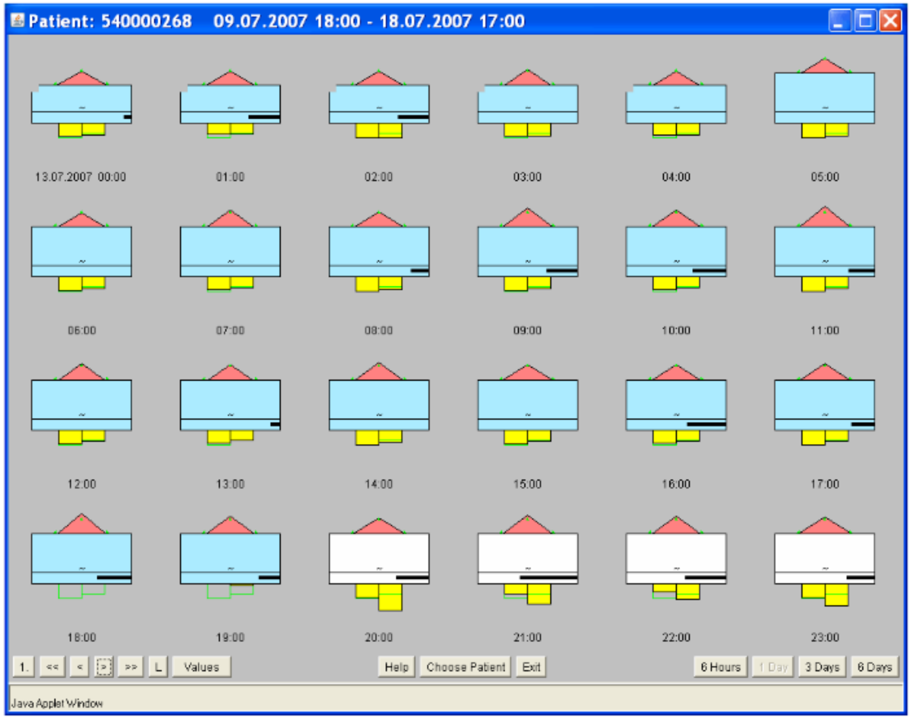
- To compare patient state in many different points in time, a compact representation is required.
- Glyphs may summarize a number of variables.
- Composite glyphs with a clear substructure are preferred for larger sets of variables.



Glyph legend: circulation, respiration and fluid balance parameters are summarized (From: Rind, 2013).

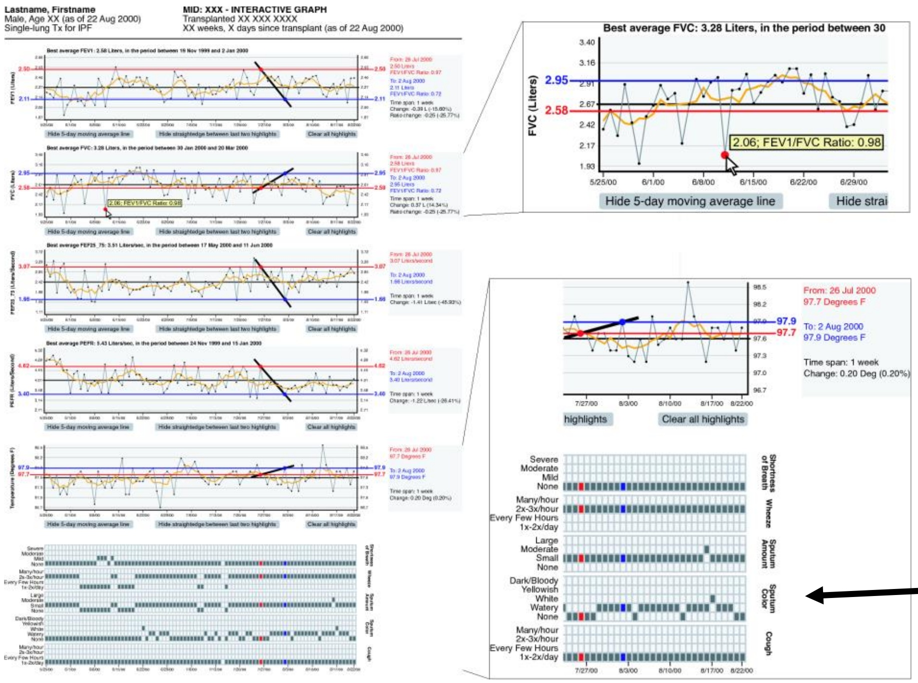
Decision Support for Clinical Treatment

Glyph-based summary of patient state:



Small multiple glyph-based visualization to display patient state over time. Needs additional views for detailed information on selected patients (From: Horn, 2001).

Decision Support for Clinical Treatment



Display of ordinal values (severe, moderate, low, none)

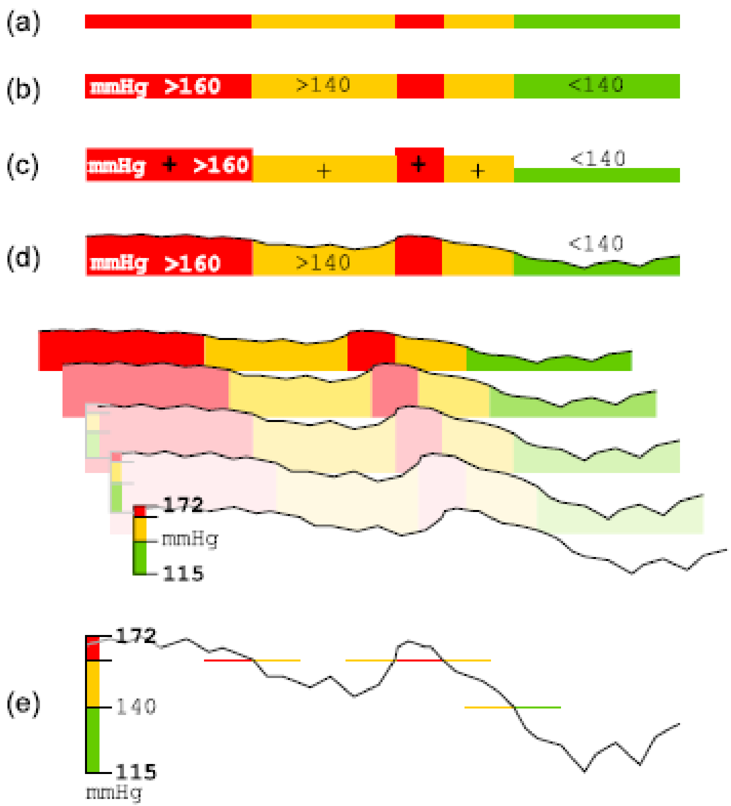
Simultaneous display of numerical and ordinal values of patient status (From: Pieczkiewicz, 2007)

Decision Support for Clinical Treatment

Midgaard: For intensive care units. Visual display of quantitative data. Semantic zoom with different levels.

(a) Color bar (red critically elevated, yellow moderately elevated), (b) with labels, (c) as bar chart, (d) with detailed temporal behavior.

Numerical data: transformed to events, when they change to elevated or critically elevated.

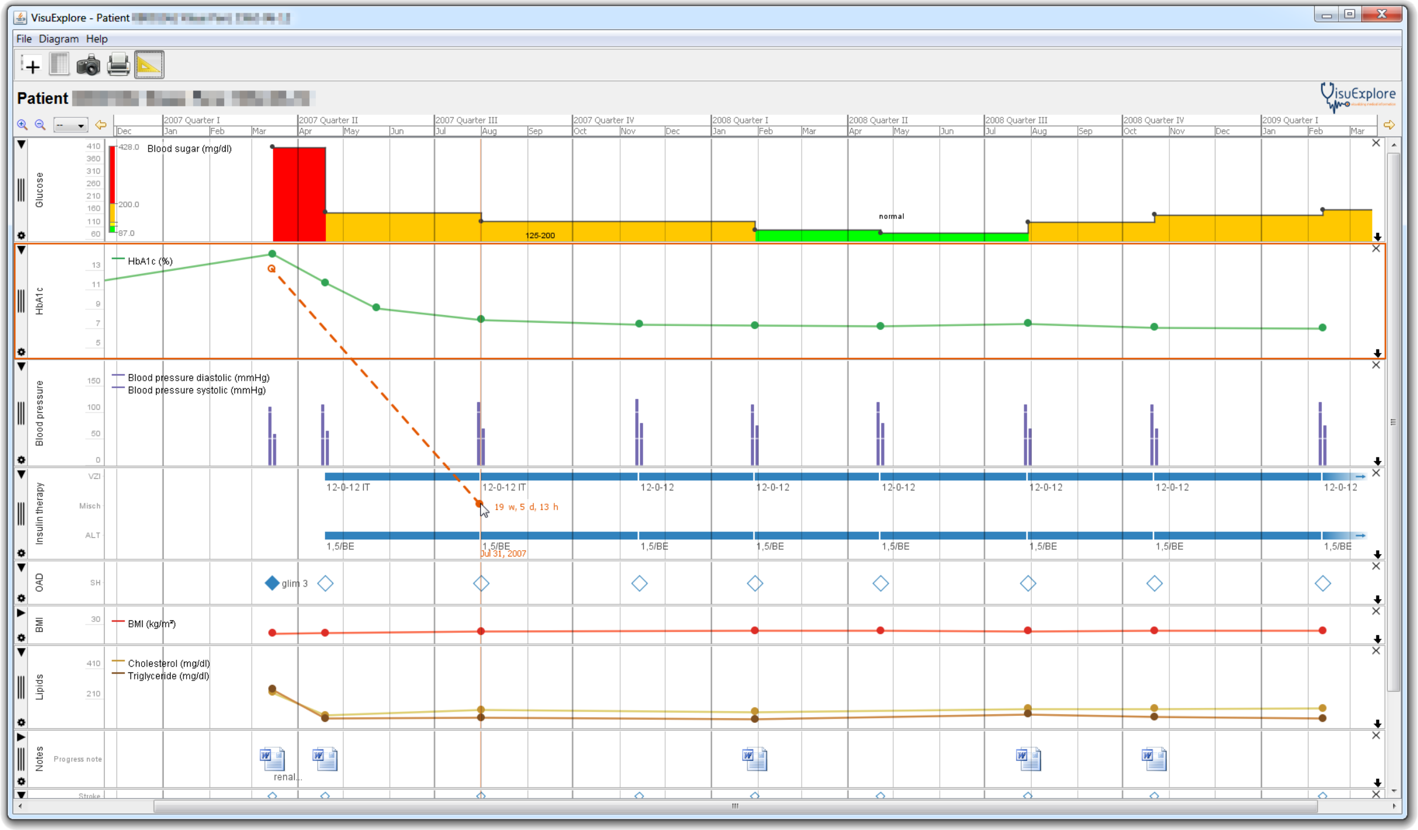


Blood pressure over time
(From: Bade, 2004).

Derived guideline: provide *parameter abstractions*

- The Midgaard-concept of translating raw temporal data to categories such as normal, elevated, … directly supports use of clinical guidelines and medical decisions based on such temporal abstractions.
- Further aggregation is possible with *temporal abstraction*, e.g. in a period of two weeks, there were elevated values in 70% of the time and critically elevated values in 10%.

Decision Support for Clinical Treatment



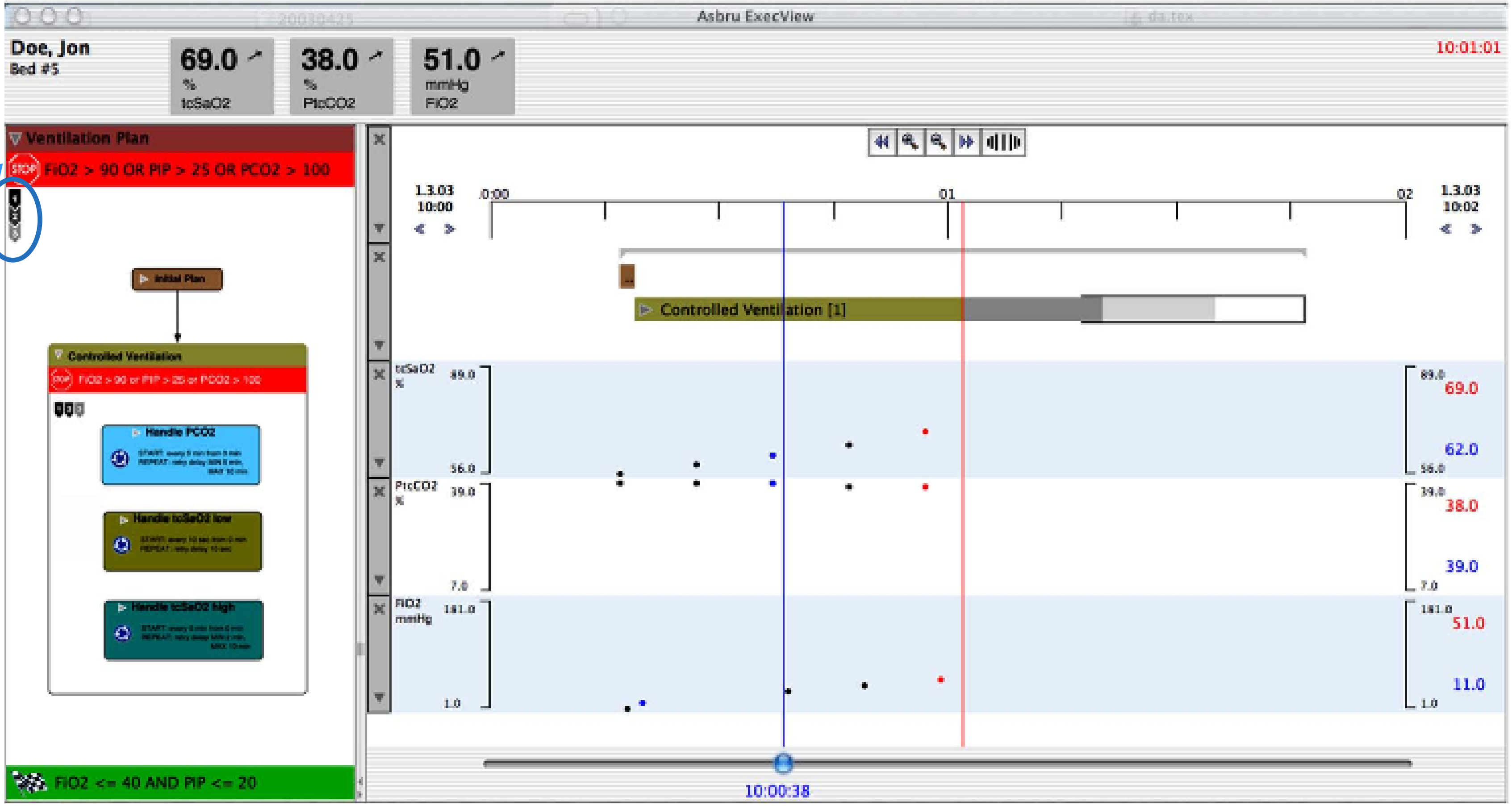
VisuExplore (Rind, 2011) based on LifeLines and Midgaard.
Provides bar charts, line and event plots to support the comparative analysis of variables (related to diabetes treatment).
Visualization techniques are simple to support intuitive use.

Decision Support: CareVis

- CareVis based on computerized medical treatment plans (Aigner/Miksch, 2006)
- Plans in XML syntax are hardly readable for physicians
- Plans should be visualized such that *hierarchy* and *temporal character* are represented
- Plans are applied to patients and the simultaneous display of the temporal structure of a treatment plan and the patient state is essential.

Decision Support : CareVis

Treatment order



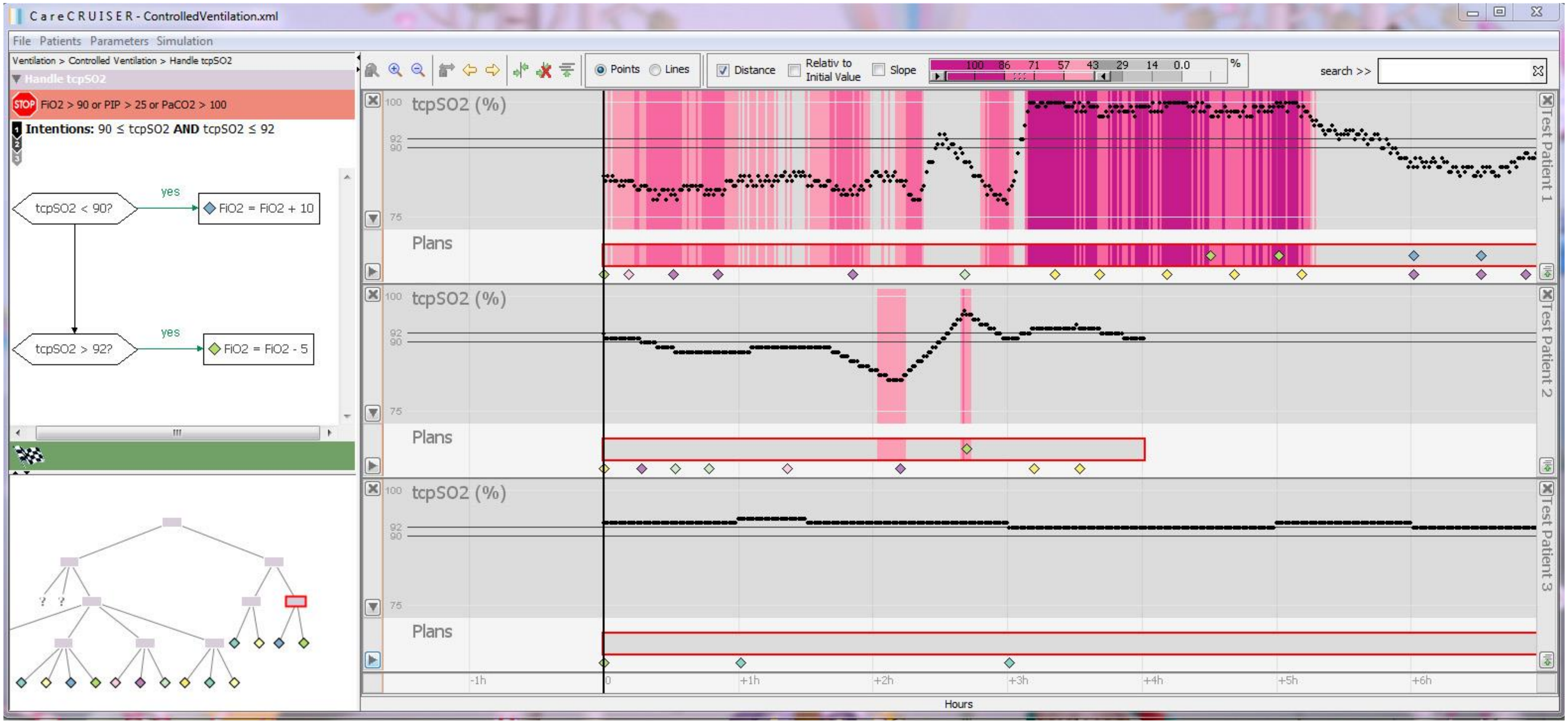
Left: logical view. **Right**: A timeline is shown along with three values for anesthesiologists monitoring a new born child in the intensive care unit (From: Aigner/Miksch, 2006).

Decision Support: CareCruiser

Extension of CareVis with the following additional requirements (Gschwandtner, 2011):

- Show how the patient evolves as a consequence of treatment
- Emphasize effects of treatment
- Enable also comparison of patients (but focus is on single patient EHR)

Decision Support: CareCruiser



Top left: Intents for the plan. Bottom left: The treatment plan with subplans. Right: patient state with unnormal values emphasized with background color (From: Gschwandtner, 2011).

Decision Support: Summary

		Tests	Diagnoses	Treatment	Details
Single EHR	LifeLines	•	•	•	Events and intervals for diverse medical information
	MIVA	•		•	Tests and treatments recorded in intensive care
	WBIVS	•			Pulmonary function and subjective symptoms
	Midgaard	•	•	•	Tests and treatments in intensive care and treatment plans
	VisuExplore	•	•	•	Tests, concomitant diseases, and treatments in chronic disease care
	VIE-VISU	•		•	Circulatory, respiratory, and fluid balance plus ventilation settings

Medical information types and medical scenarios (From: Rind, 2013)

There is a still a variety of methods to display the patients‘ history. No standardized approach emerged.

Visual Exploration of Multiple Patients

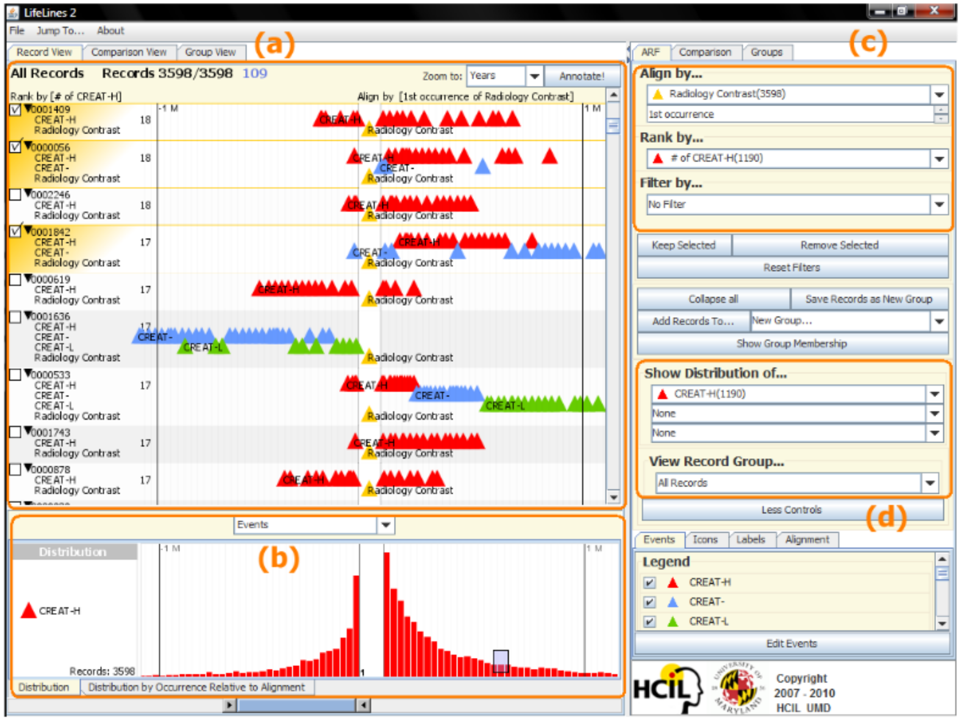
So far: adapted information visualization techniques but no analytical concepts.

Limited for few patients or data with low complexity

LifeLines2 and LifeFlow (Wang, 2010; Wongsuphasawat, 2011).

- Explore multiple patient records
- Supports alignment, ranking and filtering
- LifeFlow adds summary concepts
  - Based on common patterns datasets get reduced.
- Query mechanisms are essential to select a subpopulation, e.g. with a certain event sequence or duration

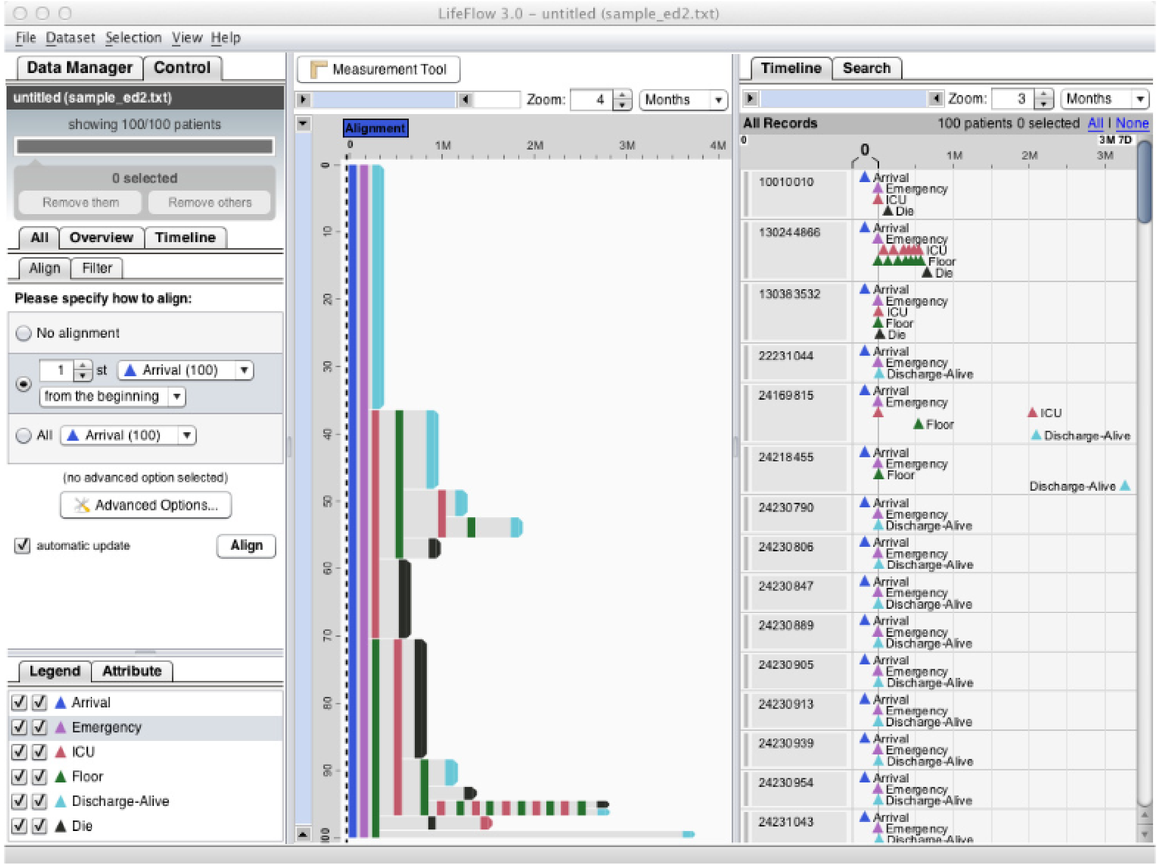
Visual Exploration of Multiple Patients



LifeLines2: Patients were selected and aligned according to a marker event, e.g. a heart attack to compare what happened before and after this event. Has been applied in a large case study (3900 patients).

(recall lect. on event sequence vis.)

Visual Exploration of Multiple Patients



LifeFlow: Overview of event sequences in 100 patients (center). Patients are aligned by arrival (From: Wongsuphasawat, 2011).

Visual Exploration of Multiple Patients

EHR collection	Lifelines2	●	●	●	Test, diagnoses, and treatment events. Numerical test events needs to be first converted to categories.
	Similan	●	●	●	Test, diagnoses, and treatment events. Numerical test events needs to be first converted to categories.
	PatternFinder	●	●	●	Test and treatment events (e.g., creatinine and contrast administration)
	VISITORS	●	●	●	Mostly test and treatments data. Both numerical and ordinal are possible. Diagnoses can be implicitly encoded by cohorts.
	Caregiver	●	○	○	Pulmonary function, subjective symptoms, and treatment groups
	IPBC	●		●	Tests and treatments recorded during dialysis sessions
	Gravi++	●	○	○	Questions and indicators in cognitive behavior therapy
	TimeRider	●	○	○	Tests, concomitant diseases, and treatments in cohorts of long-term diabetes patients

●: full support, ○: partial support, " ": no support.

Medical information types and medical scenarios (From: Rind, 2013)

Evaluation (see Rind, 2013):

- Few systems (LifeLines2, LifeFlow, Similan, PatternFinder) were evaluated in *case studies*, that is they were used for a longer time by one or few physicians to support clinical decisions.
- Very few systems (LifeLines2, Visitors) were used routinely (not for research) or were integrated in commercial systems.
- Most evaluations are user studies where instead of the target user group students were employed.

A constant result is that alignment features are crucial.

Identification of Adverse Drug Effects

- Definition: „an injury event resulting from medical intervention related to a drug“

- Motivation:
  - Drugs get misused, interact with each other and may cause severe effects, e.g. due to an allergy
  - In the US, 800.000 adverse drug effects are registered annually, leading to 98.000 deaths.
  - Increasing awareness and initiatives to improve patient safety.
  - Patients get older and older persons tolerate drugs less.
  - Comorbidity and other drugs increase the problem.

→ „significant reduction of preventable ADE is a challenging issue in public health (Baceanu, 2009)

Identification of Adverse Drug Effects

- Data:
  - The FDA provides an Adverse Event Reporting System. Records contain: drugs, indication (why the drug is given), reaction, socio-demographic data (age, sex, BMI) (Mittelstädt, 2014)
  - Hospitals collect EHRs which document hospital stays including medication, diagnosis, procedures, lab results
  - Reports (free text), e.g. dismission letters
  - is always anonymized
- Requirements:
  - Provide an overview of the data to detect anomalies and patterns
  - Enable flexible filtering w.r.t. combinations of drugs and indication
  - Incorporate analytics
  - Support report generation

Hospital 4, Stay 1778

Return to previous page | REPORT

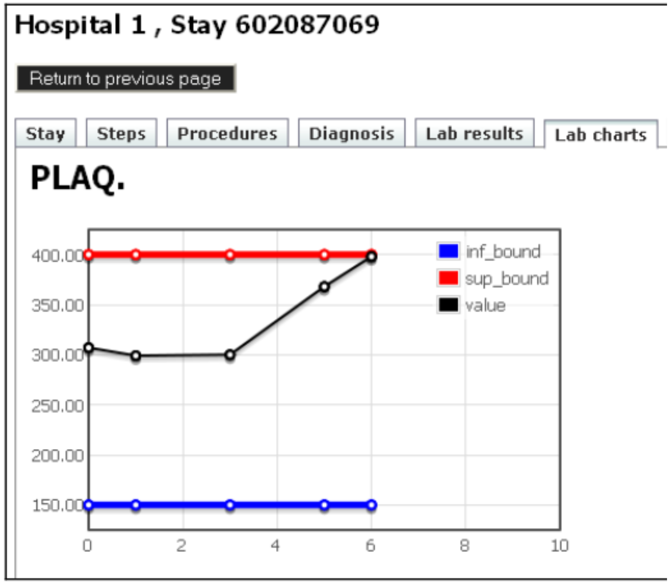
Stay | Steps | Acts | Diagnosis | Biology | Drugs | Documents

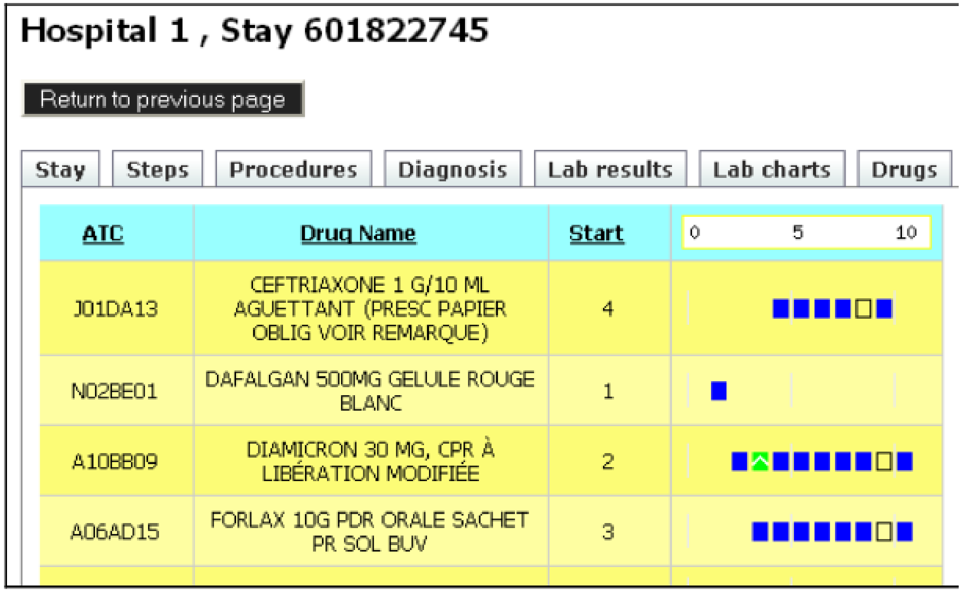
Age	82.601
Sex	female
Death	no
Death Expectation	
Duration	34 days
Expected Duration	days
Principal Diagnosis	ICD10 = R189
Number of different theoretical MDCs (Major Diagnosis Categories)	1
Number of different associated diagnosis	1
Number of different acts	12

Medical units visited	1
Back and Forth between medical units	no
Delay next hospitalisation	
Transfer to another "short hospitalisation" hospital	no
Through ICU	no
Through ICU Expectation	
ICU Duration	0 days
Expected ICU Duration	days
Gravity score (SAPS)	
Delay before ICU	days

Summary of a hospital stay (From: Baceanu, 2009).

Adverse Drug Effects: Overview



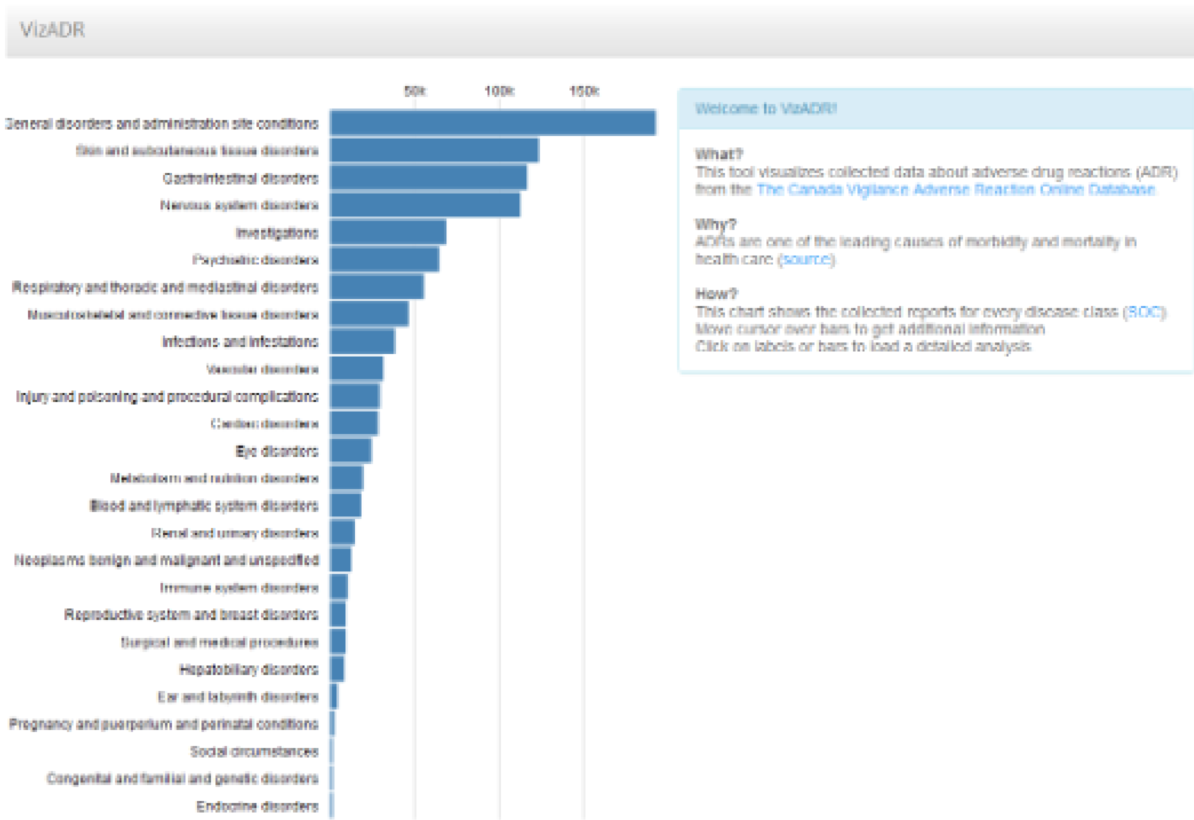


Lab and drug charts add further information (From: Baceanu, 2009).

For further exploration: specify detection rules (combinations with logical operators and negation) to get a list of matching hospital stays for further analysis and report generation.

In a *guided* fashion, users answer a couple of questions used for reports.

Adverse Drug Effects: Overview



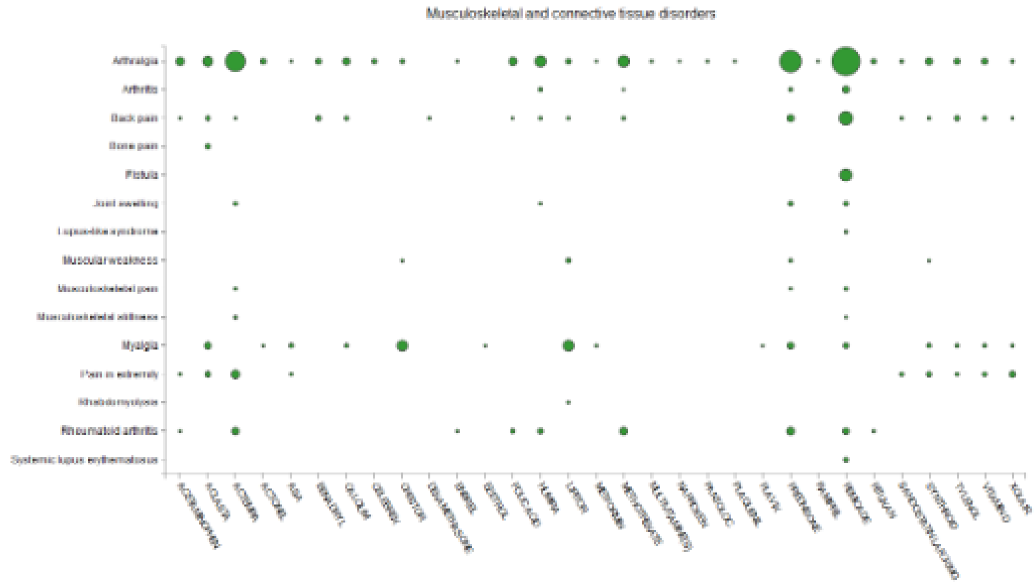
Frequency of adverse effects (From: Pfundner, 2016).

Classes may be selected for further analysis.

Backpain

Muscular weakness

Rheumatoid arthritis

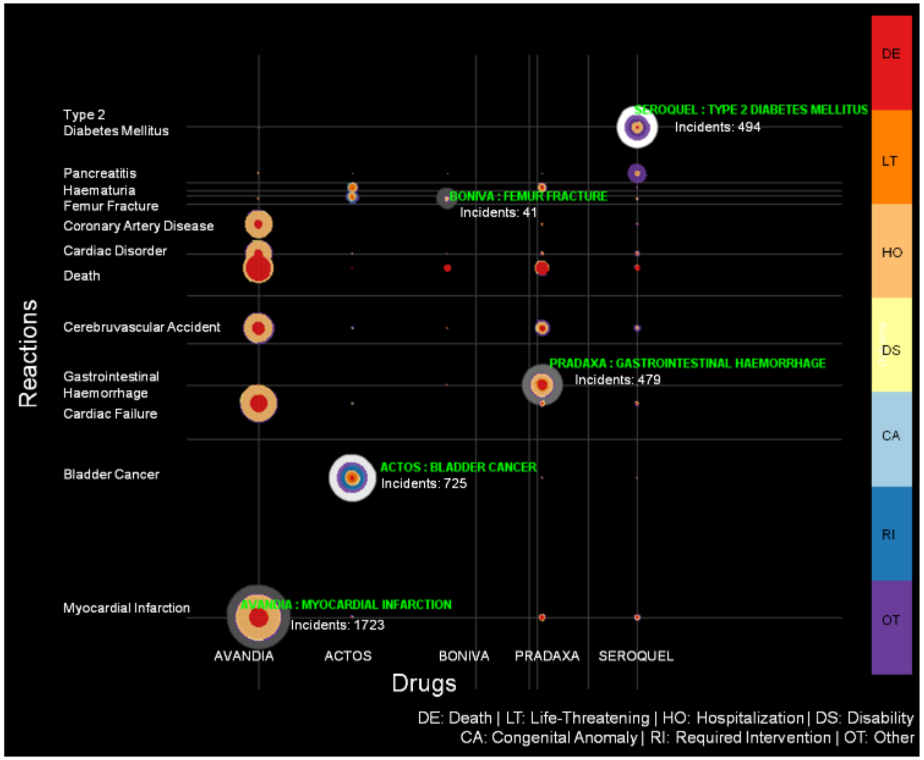


Scatterplot between drug and adverse reaction. Size encodes frequency (From: Pfundner, 2016).

Limitations: Severity of adverse effects not considered, for only small sizes of the database.

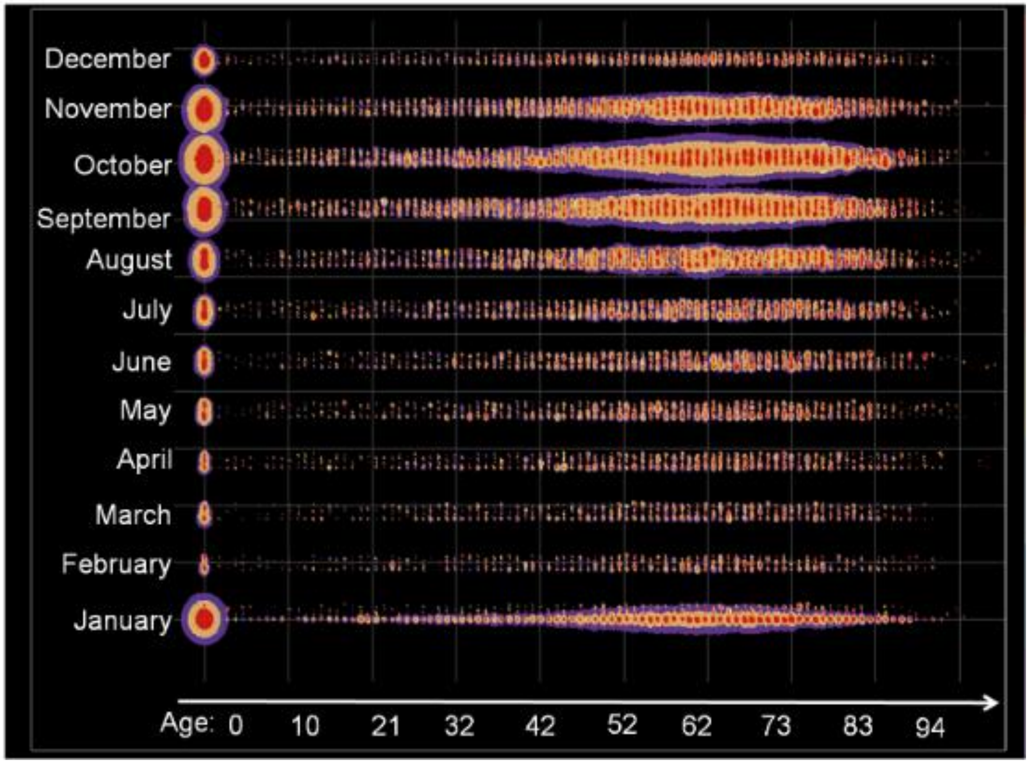
Additions: Sorting, filtering (gender, age interval, seriousness)

Adverse Drug Effects: Overview



Seriousness is encoded as ordinal attribute with hospitalization (HO), life threatening (LT) and death (DE) as most urgent. A color scale (temperature metaphor) is used to reveal seriousness and direct towards more serious events (From: Mittelstädt, 2014).

Adverse Drug Effects: Overview

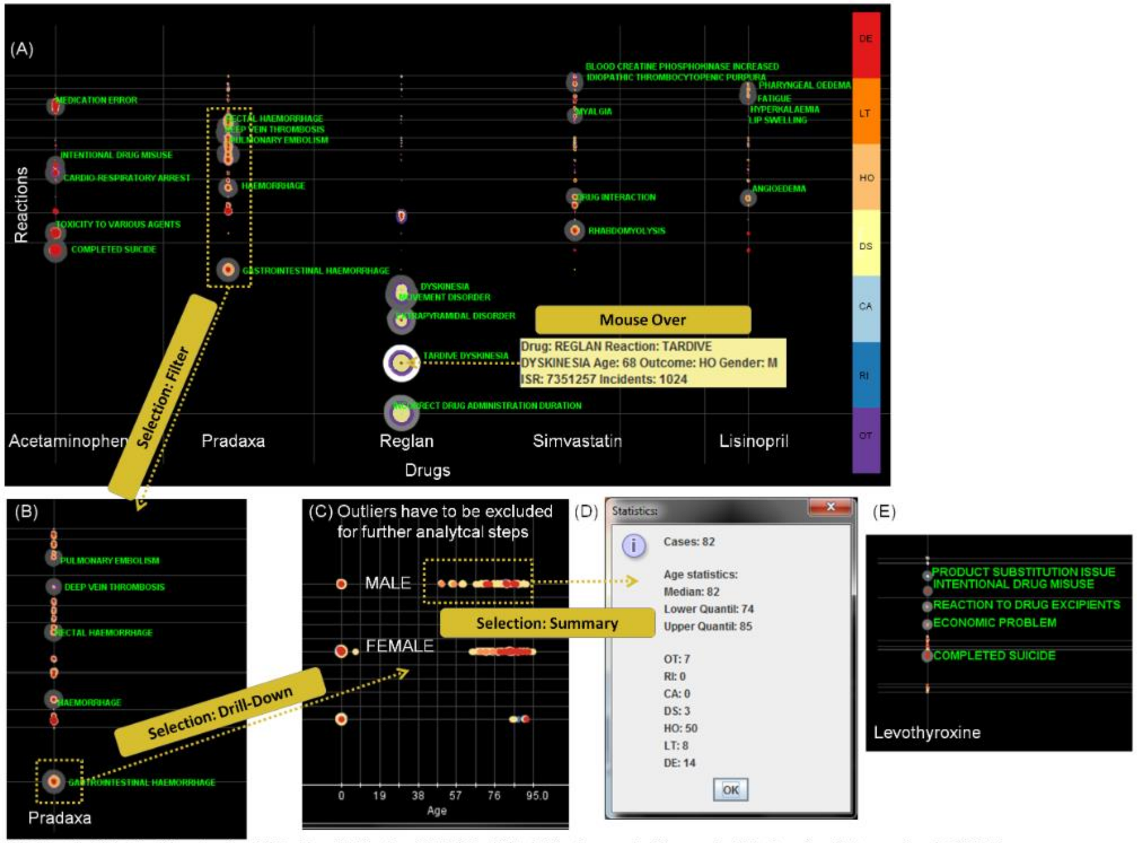


A scatterplot with patient age, months of the year and color encoding severity of ADEs provides a further overview for a selected drug (From: Mittelstädt, 2014).

Identification of Adverse Drug Effects

- Statistical tools are limited to detecting events with predefined frequency thresholds.
- Interpretation is challenging due to confounders.
  - Myocardial infarct is a typical complication of diabetes.
  - A patient with diabetes receives a new drug and suffers later from a myocardial infarct. What is the causality?
- Due to the confounders, fully automatic systems are limited. → Interactive visual analysis is promising.

Identification of Adverse Drug Effects



DE: Death | LT: Life-Threatening | HO: Hospitalization | DS: Disability | CA: Congenital Anomaly | RI: Required Intervention | OT: Other

Overview, selection, detail and numerical attributes. Stepwise and refined analysis of ADEs. Pradaxa leads to hemorrhage and death in this ageing patient group (From: Mittelstädt, 2014).

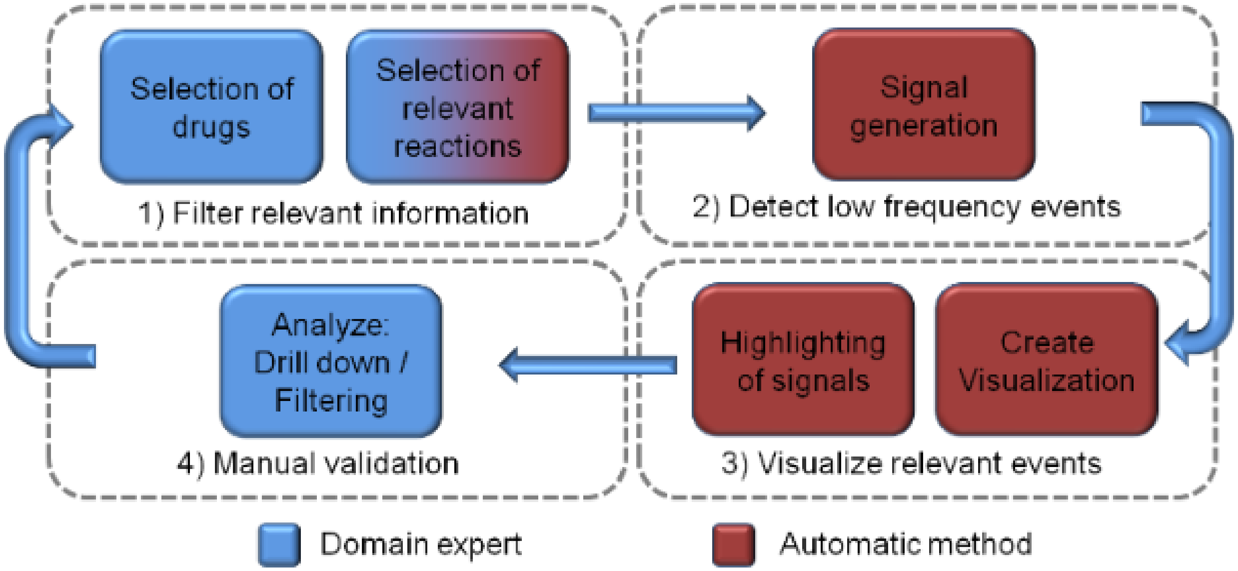
Identification of Adverse Drug Effects

Analytic tasks:

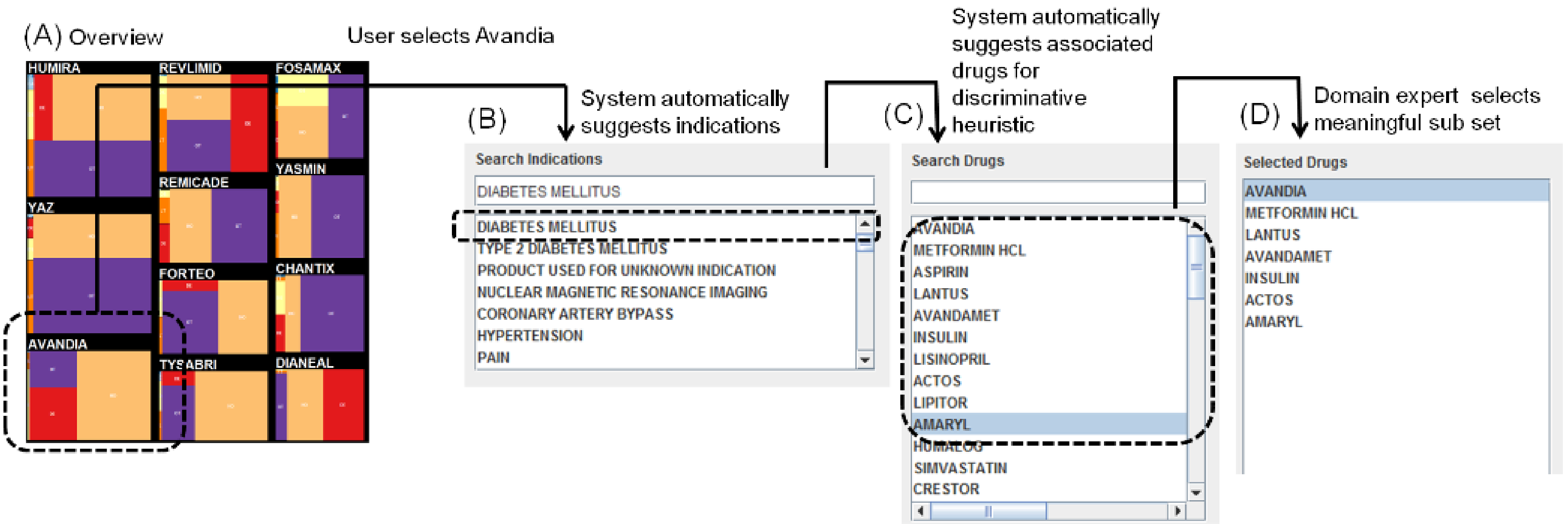
- Explore relevant adverse effects
- Explore gender and age distribution for relevant ADEs
- Summarize demographic information
- Validation of identified effects

Requirements:

- Interactive filtering of relevant information
- Low frequency events should be detected automatically
- Visual interfaces must highlight relevant candidates



Stepwise approach combining user input (blue) and automatic methods (red) (From: Mittelstädt, 2014)



Based on an overview, one drug, most frequently related in-dications, alternative drugs are explored with a mixture of user-defined selection and automatic control (From: Mittelstädt, 2014).

Identification of Adverse Drug Effects

Analytics:

- Association rules and decision trees are used to detect events (Chazard, 2009 and 2011)

Alternative:

Compute Odds-Ratio and Compare with related drugs

$$odds(x,y) = \frac{a^2 \cdot d}{(b+1)\cdot(c+1)} \qquad (1)$$

	Reaction Y	Other Reactions
Drug X	a	b
Other Drugs	c	d

If „a“ and „d“ have high values; „b“ and „c“ have low values, „odds“ gets high values indicating elevated risk.

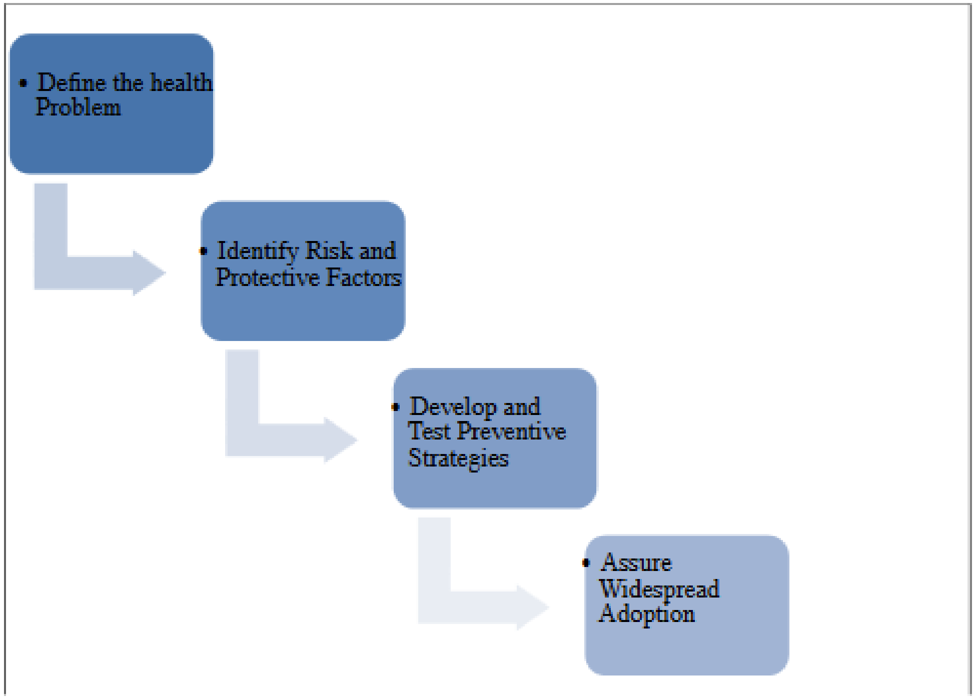
Identification of Adverse Drug Effects

Use of analytic results:

- Drugs may be *filtered* to ensure a minimum number of ADEs (for statistical significance) and *ordered* according to the Odds-ratio to find the most severe problems in a whole database or for a family of drugs.

Visual Analytics for Public Health

- Based on large, standardized data collections with substantial quality control (not possible in clinical routine)
- Focussed on analyzing disease spread, risk factors, nutrition behavior
- Support of health policy makers
  - Start campaigns, preventive examinations, …
- Consider two examples:
  - Infection spread
  - Nutrition behavior



4-Stage model of public health (From: Al-Hajj, 2013).

Epidemic Modeling

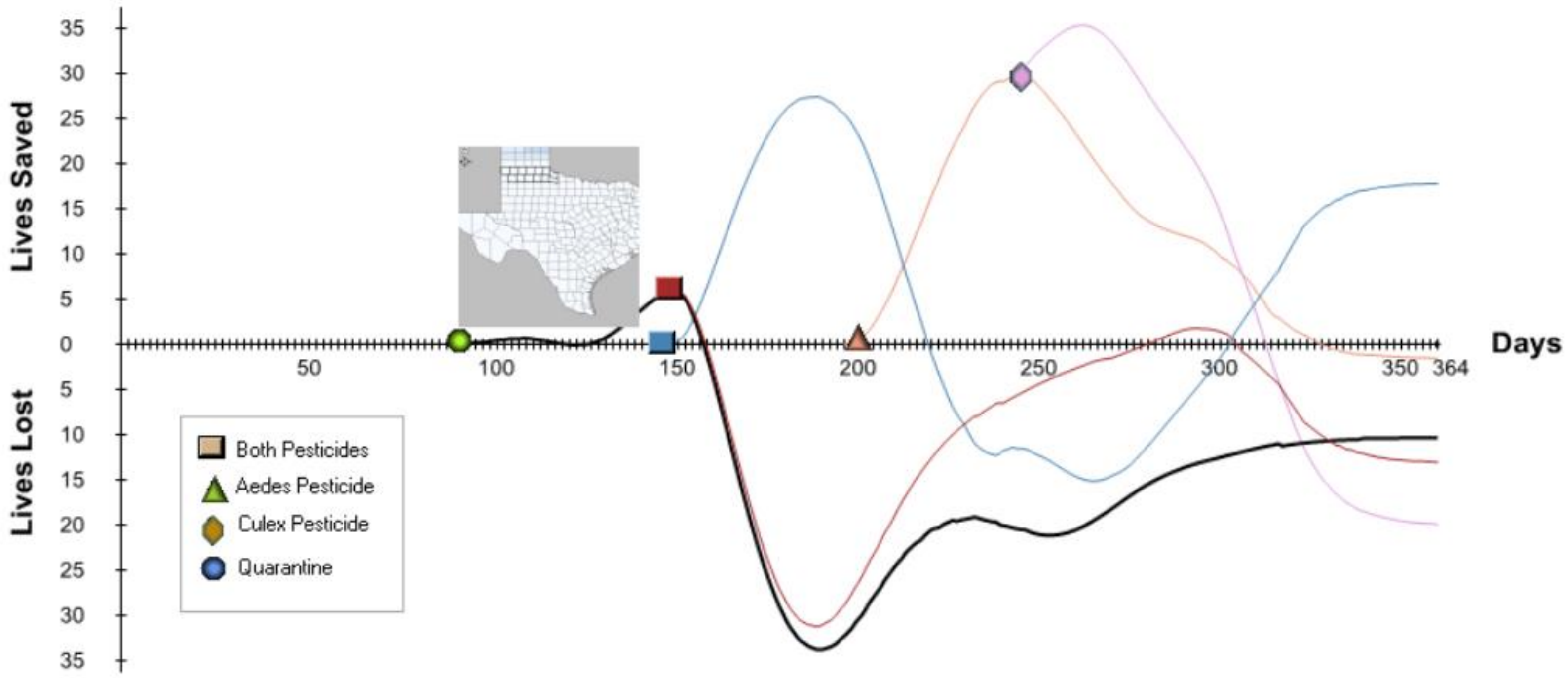
- Modeling of infectious diseases aims at predicting spatio-temporal course of an outbreak and impact of response measures, such as closure of schools, vaccination, public alerts
- Visual analytics may provide decision support based on a simulation of infection spread
  - Input data: age distribution, publication density, subtype of disease
  - Output data: number and percentage of people that get sick, need hospitalization or die
- Involves a number of challenges (recall Shneiderman, 2013), e.g. risks and uncertainty, team decisions

Epidemic Modeling

Example (Afzal, 2011):

- Modeling disease spread based on established model, incorporating airtraffic (Elveback, 1976)
- Enable users to insert response measures at any time
- See the short term and long term effects of these measures in terms of lives saved/loss …
- Extended history view essential. Study and compare different response plans (remember in clinical decision making we had treatment plans)

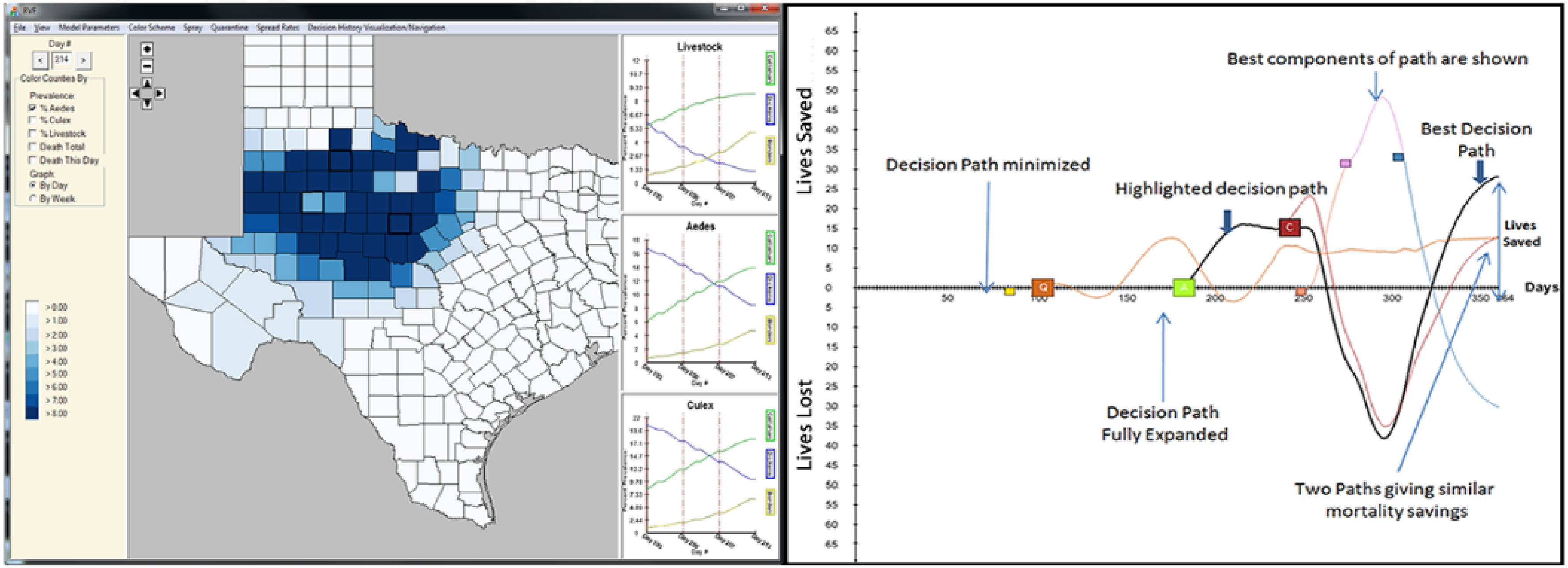
Epidemic Modeling



Different scenarios of infection spread with decision points and their effect (on different scales). (From: Afzal, 2011). Uncertainty, is not conveyed.

Visual Analytics for Public Health

Epidemic Modeling



Left: spatio-temporal view (with a slider different points in time are adjusted). Right decision paths and their consequences (From: Afzal, 2011).

For more details on spatio-temporal modeling of infection spread, see [Bryan, 2015]

Prevention of Injuries

For younger persons (until 45), injuries are the most important cause of death and disability.

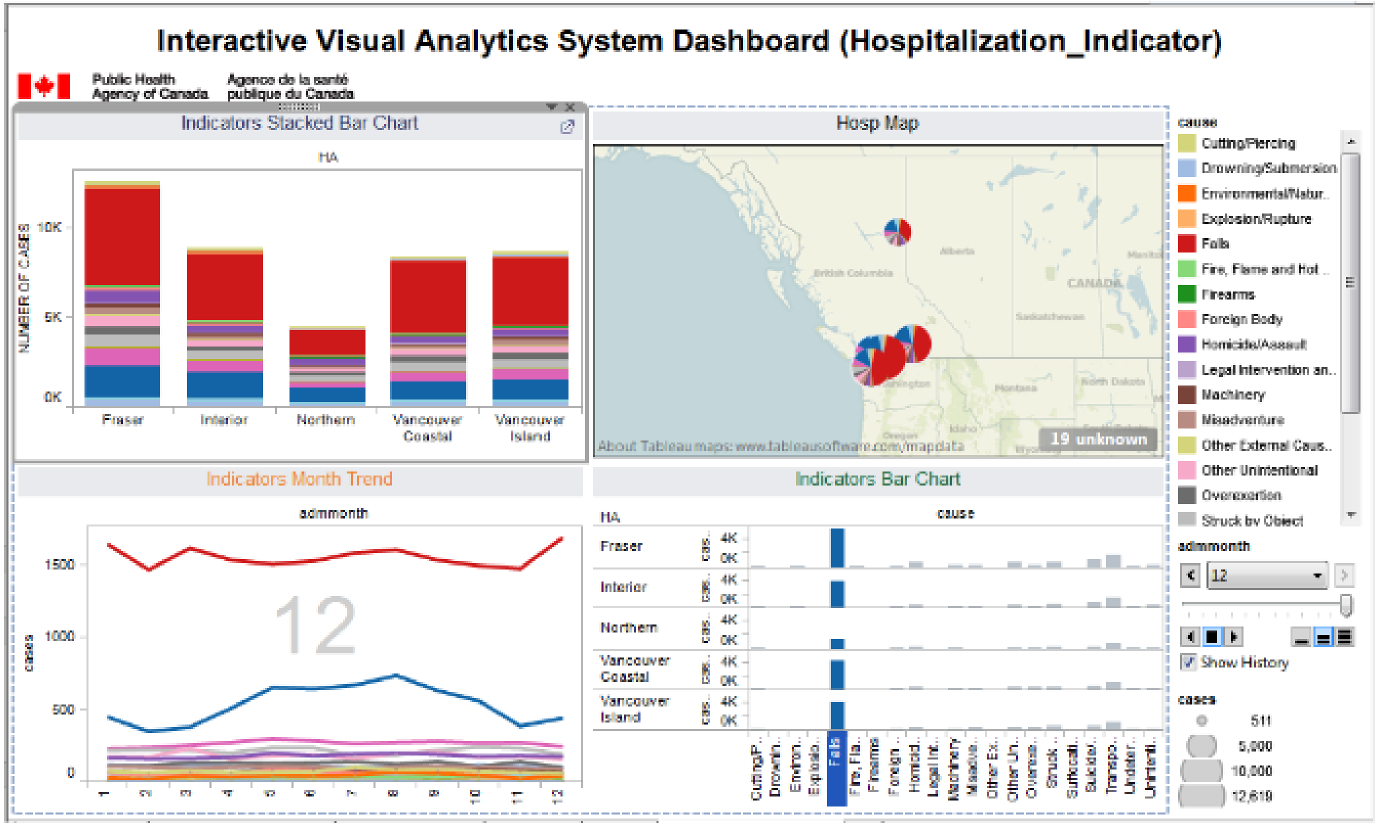
High costs for hospitalization and home health care.

Careful analysis

- how types of injuries change over time in frequency and severity
- Where injuries occur particularly often
- Which age group is particularly affected.

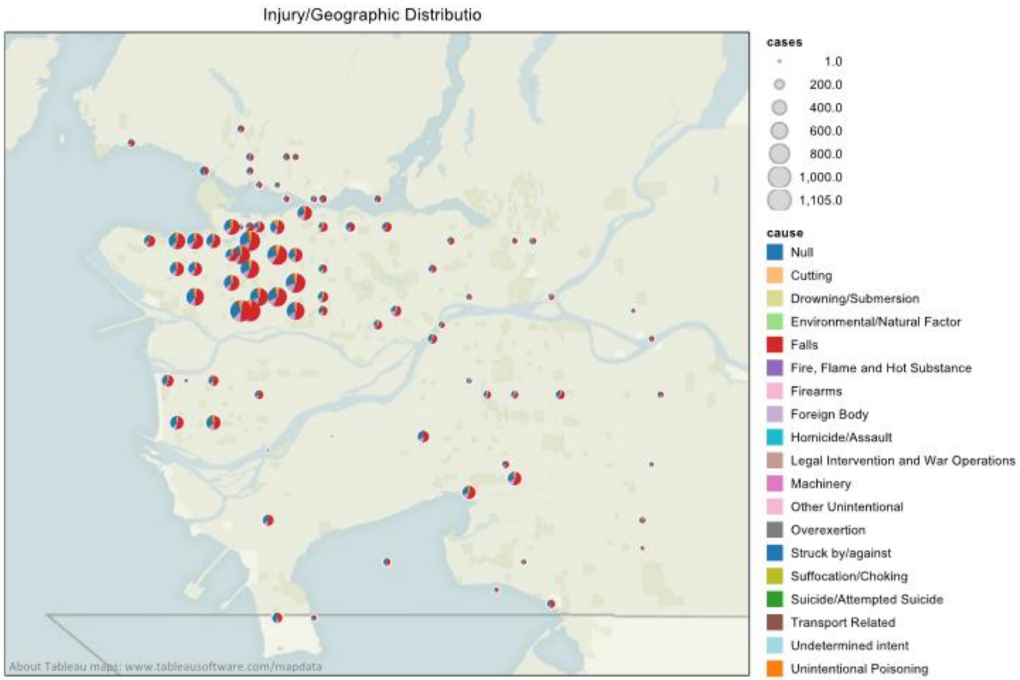
Consequences: Advice constructions of playgrounds, devices for sport, e.g. skateboards, helmets for bikers, start public campaigns

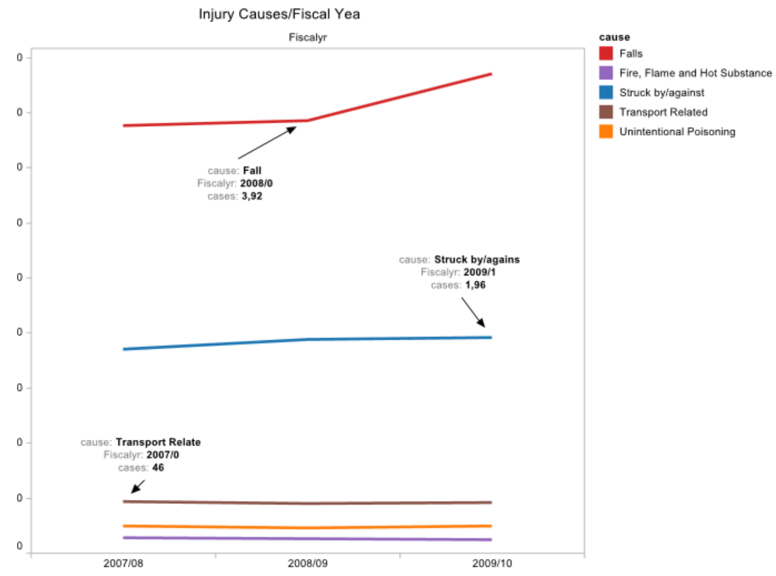
Prevention of Injuries



Dashboard for showing injury data with 4 views; geospatial, trends and two stacked bar charts (From: Al-Hajj, 2013)

Prevention of Injuries

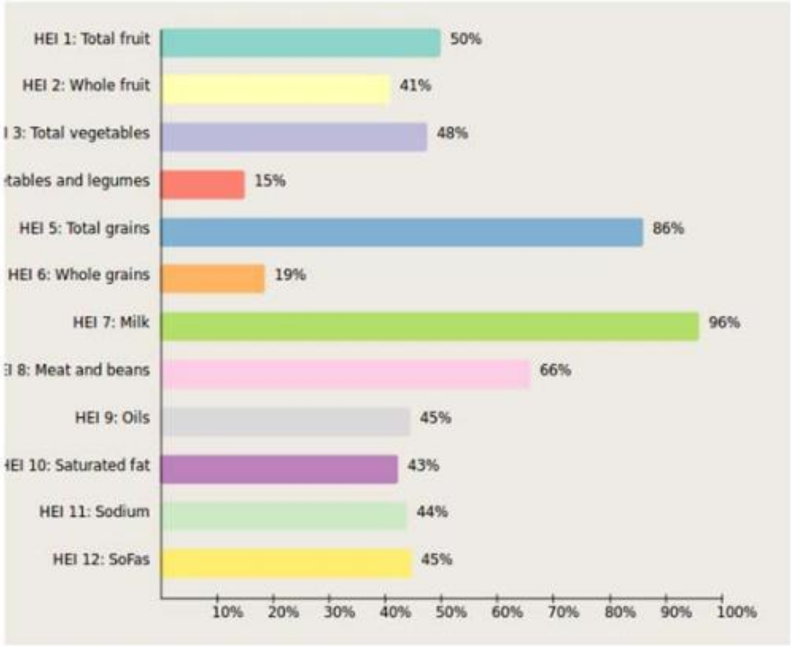


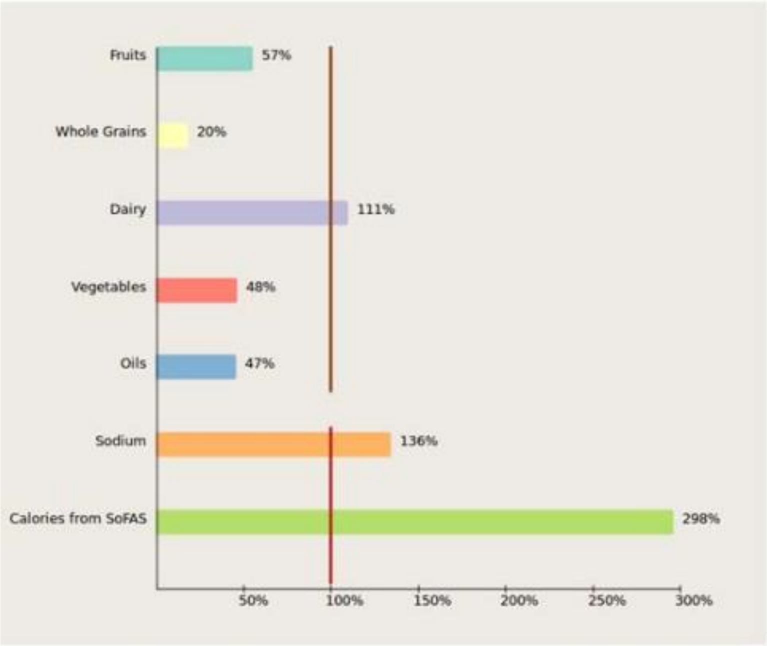


Left: Spatial view, right: temporal changes in the top 5 causes of injury.

Visual Analytics of Nutrition Behavior Data

- Questionaires related to nutrition in the last 48 hours were collected (Torres, 2012)
- Food was categorized in 12 categories
- Demographic data available (e.g. age, gender, employment, …)
- Analysis of relations between food categories, investigation of subpopulations, deviations to Dietary Guidelines for Americans (DGA) from the Health and Human Services
- Users can explore clusters (k-means), selection from clusters, persons in different regions and analyze nutrition





Left: Nutrition in 12 categories. Right: transformation to 7 categories related to the guidelines with two markers: top: this amount SHOULD be consumed; bottom: this amount should NOT BE EXCEEDED.

HEI 12: solid fats, alcoholic beverages, and added sugars

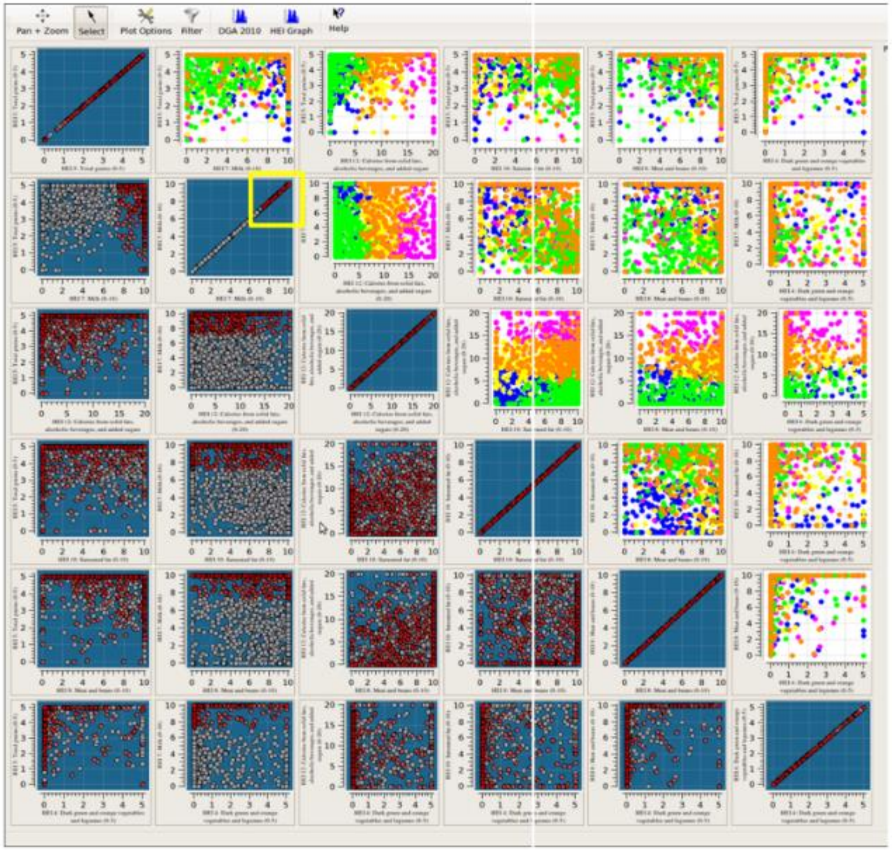
(From: Torres, 2012)

Visual Analytics of Nutrition Behavior Data

An enhanced scatterplot matrix reveals correlations between food components.

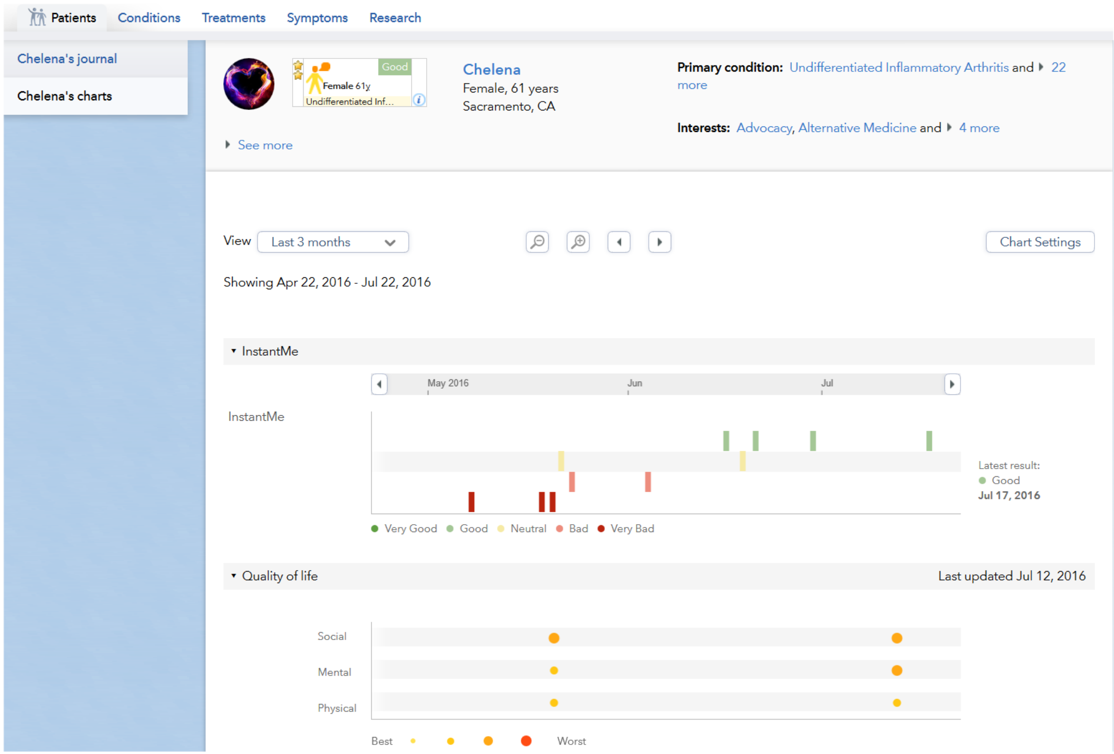
Upper diagonal elements displays a projected clustering result.

6x6 matrices turned out to be useable (From: Torres, 2012).

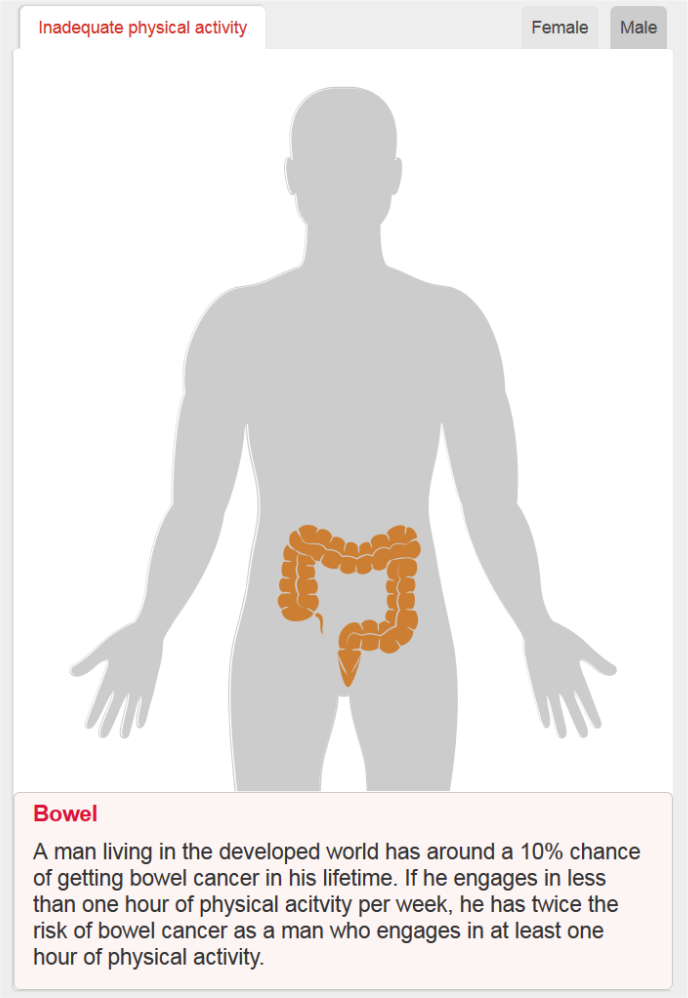


Patient Information and Comparison

With information visualization, patients may provide their health status, meet with others having similar problems and exchange. „patients like me“.



Interactive Body Map: What Really Gives You Cancer



Link

Summary

- Visual Analytics solutions enable decision support for clinical treatment by summarizing information related to patient conditions, variants of treatment, complications and prognosis.
  - Temporal character of events plays an essential role.
  - Temporal and parameter abstraction are crucial for overviews.
- Visual Analytics of cohort study data supports the search for risk factors and interactions between risk factors by combining overview visualizations, clustering, statistics, and statistical graphics.
  - Although cohort study data is often longitudinal, analysis so far is often restricted to one cycle, since measurements and treatments and even non-medical conditions change over long periods considerably.

Summary

- Data are primarily shown along a common horizontal zoomable timeline.
- Facetting (LifeLines) is essential to collapse/hide (ir)relevant information; e.g. treatment, diagnosis, lab values
- Filtering involves non-temporal constraints (age, sex) and time-and-value constraints (increase in blood pressure)
- Multi-patient data exploration and display involves special filtering for patients, techniques for aggregating patients

Summary

„Discovering knowledge in complex high-dimensional datasets needs a concerted effort of various topics, ranging from data preprocessing, data fusion, data integration and data mapping to interactive visualization in lower-dimensional space“ (Hund, 2015).

In healthcare, knowledge discovery is focussed on

- decisions physicians have to make or
- research questions of epidemiologists or
- decisions of health policy makers related to the use of drugs and other treatment options.

Future Work

- Better support for web-based and mobile access
  - Mobile access requires even more different granularities and powerful aggregation (first attempts)
- Systems for decision support need to be evaluated w.r.t. influence on decisions
  - How do visualization, interactive exploration and analytics influence decisions?
  - How do decisions change compared to using standard presentations, e.g. unstructured text and tables
- Long-term studies are needed (diaries of use)
- Better for communicating results (report generation)
- Systems are hard to compare, since no shared data and tasks are available
  - A repository with anonymized EHR data is necessary.

References

S. Afzal, R. Maciejewski, D. S. Ebert: Visual analytics decision support environ-ment for epidemic modeling and response evaluation. *Proc. of IEEE VAST* 2011: 191-200

W. Aigner, S. Miksch: CareVis: Integrated visualization of computerized protocols and temporal patient data. *Artificial Intelligence in Medicine* 37(3): 203-218 (2006)

S Al-Hajj, I Pike, B Fisher. Interactive Dashboards: Using Visual Analytics for knowledge Transfer and Decision Support, *IEEE Visual Analytics Science and Technology*, 2013

P. Angelelli, S. Oeltze, J. Haasz, C. Turkay, E. Hodneland, Arvid Lundervold, Astrid J. Lundervold, B. Preim, H. Hauser: Interactive Visual Analysis of Heterogeneous Cohort-Study Data. *IEEE Computer Graphics and Applications* 34(5): 70-82 (2014)

A. Băceanu, I. Atasiei, E. Chazard, N. Leroy, The Expert Explorer: A Tool for Hospital Data Visuali-zation and Adverse Drug Event Rules Validation, Stud Health Technol Inform, 148, (2009), 85–94

R. Bade, S. Schlechtweg, and S. Miksch, “Connecting time-oriented data and information to a coherent interactive visualization,” in *Proc. of ACM SIGCHI Conference on Human Factors in Computing Systems*, pp. 105–112, 2004

Chris Bryan, Xue Wu, Susan M. Mniszewski, Kwan-Liu Ma: Integrating predictive analytics into a spatiotemporal epidemic simulation. VAST 2015: 17-24

Elveback LR, Fox JP, Ackerman E, Langworthy A, Boyd M, Gatewood L. An influenza simulation model for immunization studies*, Am J Epidemiol.* 1976 Feb;103(2):152-65.

A. Faiola and C. Newlon, “Advancing critical care in the ICU: A Human-Centered biomedical data visualization systems,” in *Proc. of Human-Computer Interaction*, pp. 119–128, Springer, 2011.

T. Gschwandtner, W. Aigner, K. Kaiser, S. Miksch, A. Seyfang (2011): CareCruiser: Exploring and visualizing plans, events, and effects interactively. *Proc. of PacificVis* 2011, pp. 43-50

Hesse, B.W.; Hansen, D.; Finholt, T.; Munson, S.; Kellogg, W.; Thomas, J.C., Social Participation in Health 2.0, IEEE Computer, Vol. 43(11): 45-42, 2010

References (II)

M. Hund, W. Sturm, T. Schreck, T. Ullrich, D. A. Keim, L. Majnaric, A. Holzinger (2015): Analysis of Patient Groups and Immunization Results Based on Subspace Clustering. In: (book) Brain Informatics and Health, pp. 358-368

S. Mittelstädt, M. C. Hao, U. Dayal, M. Hsu, J. Terdiman, D. A. Keim (2014). Advanced visual analytics interfaces for adverse drug event detection. *Proc. of AVI*, pp. 237-244

Monroe, M., Wongsuphasawat, K., Plaisant, C., Shneiderman, B., Millstein, J., & Gold, S. "Exploring point and interval event patterns: Display methods and interactive visual query." *University of Maryland Technical Report* (2012).

S. Oliveros Torres, H. A. Eicher-Miller, C. J. Boushey, D. S. Ebert, R. Maciejewski. „Applied Visual Analytics for Exploring the National Health and Nutrition Examination Survey“. *HICSS* 2012: 1855-1863

A. Pfundner, J. Kuric (2016). „VizADR - Visualizing Adverse Drug Reactions“, Student Report, Vienna University

D. Pieczkiewicz, S. M. Finkelstein, and M. I. Hertz, “Design and evaluation of a web-based interactive visualization system for lung transplant home monitoring data,” in *Proc. of the AMIA 2007 Symposium*, pp. 598–602, 2007.

M. Pohl, S. Wiltner, A. Rind, W. Aigner, S. Miksch, T. Turic, F. Drexler: Patient Development at a Glance: An Evaluation of a Medical Data Visualization. *INTERACT* (4) 2011: 292-299

Seth M. Powsner and Edward R. Tufte. Graphical Summary of Patient Status. *The Lancet*, 344(8919):386-389, August 1994.

References (III)

A. Rind, W. Aigner, S. Miksch, S. Wiltner, M. Pohl, T. Turic, and F. Drexler. “Visual exploration of time-oriented patient data for chronic diseases: Design study and evaluation,” in *Information Quality in e-Health, Proc.of the USAB 2011*, pp. 301–320, 2011.

A. Rind, T. D. Wang, W. Aigner, S. Miksch, K. Wongsuphasawat, C. Plaisant, and B. Shneiderman (2013). Interactive Information Visualization to Explore and Query Electronic Health Records. *Found. Trends Hum.-Comput. Interact.* 5, 3: 207-298.

Ben Shneiderman, Catherine Plaisant, Bradford W. Hesse, "Improving Healthcare with Interactive Visualization", *Computer*, Vol.46(5):58-66, 2013

C. Turkay, F. Jeanquartier, A. Holzinger, H. Hauser: On Computationally-Enhanced Visual Analysis of Heterogeneous Data and Its Application in Biomedical Informatics. *Interactive Knowledge Discovery and Data Mining in Biomedical Informatics* 2014: 117-140

C. Turkay, Arvid Lundervold, Astrid Johansen Lundervold, H. Hauser: Hypothesis Generation by Interactive Visual Exploration of Heterogeneous Medical Data. *Proc. of CHI-KDD* 2013: 1-12

C. Turkay, Arvid Lundervold, Astri J. Lundervold, H. Hauser: Representative Factor Generation for the Interactive Visual Analysis of High-Dimensional Data. *IEEE Trans. Vis. Comput. Graph.* 18(12): 2621-2630 (2012)

T. D. Wang. Interactive visualization techniques for searching temporal categorical data. In Ph.D. thesis, Dept. of Computer Science, University of Maryland, 2010

K. Wongsuphasawat, J. Ǵomez, C. Plaisant, T. D. Wang, M. Taieb-Maimon, and B. Shneiderman. Lifeflow: Visualizing an overview of event sequences. In Proc. of ACM SIGCHI, pages 1747–1756. ACM, 2011