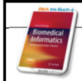

Andreas Holzinger

VO 709.049 Medical Informatics

02.12.2015 11:15-12:45

Lecture 08

Biomedical Decision Making: Reasoning and Decision Support

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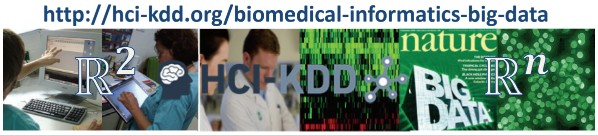
http://hci-kdd.org/biomedical-informatics-big-data



Schedule

- 1. Intro: Computer Science meets Life Sciences, challenges, future directions
- 2. Back to the future: Fundamentals of Data, Information and Knowledge
- 3. Structured Data: Coding, Classification (ICD, SNOMED, MeSH, UMLS)
- 4. Biomedical Databases: Acquisition, Storage, Information Retrieval and Use
- 5. Semi structured and weakly structured data (structural homologies)
- 6. Multimedia Data Mining and Knowledge Discovery
- 7. Knowledge and Decision: Cognitive Science & Human-Computer Interaction
- **8. Biomedical Decision Making: Reasoning and Decision Support**
- 9. Intelligent Information Visualization and Visual Analytics
- 10. Biomedical Information Systems and Medical Knowledge Management
- 11. Biomedical Data: Privacy, Safety and Security
- 12. Methodology for Info Systems: System Design, Usability & Evaluation

Keywords of the 8th Lecture

- Artificial intelligence
- Case based reasoning
- Computational methods in cancer detection
- Cybernetic approaches for diagnostics
- Decision support models
- Decision support system (DSS)
- Fuzzy sets
- MYCIN
- Radiotherapy planning

Advance Organizer (1)

- **Case-based reasoning (CBR)** = process of solving new problems based on the solutions of similar past problems;
- **Certainty factor model (CF)** = a method for managing uncertainty in rule-based systems;
- **CLARION =** Connectionist Learning with Adaptive Rule Induction ON-line (CLARION) is a cognitive architecture that incorporates the distinction between implicit and explicit processes and focuses on capturing the interaction between these two types of processes. By focusing on this distinction, CLARION has been used to simulate several tasks in cognitive psychology and social psychology. CLARION has also been used to implement intelligent systems in artificial intelligence applications.
- **Clinical decision support (CDS)** = process for enhancing health-related decisions and actions with pertinent, organized clinical knowledge and patient information to improve health delivery;
- **Clinical Decision Support System (CDSS)** = expert system that provides support to certain reasoning tasks, in the context of a clinical decision;
- **Collective Intelligence** = shared group (symbolic) intelligence, emerging from cooperation/competition of many individuals, e.g. for consensus decision making;
- **Crowdsourcing** = a combination of "crowd" and "outsourcing" coined by Jeff Howe (2006), and describes a distributed problem-solving model; example for crowdsourcing is a public software beta-test;

Advance Organizer (2)

- **Decision Making** = central cognitive process in every medical activity, resulting in the selection of a final choice of action out of several alternatives;
- **Decision Support System (DSS)** = is an IS including knowledge based systems to interactively support decision-making activities, i.e. making data useful;
- **DXplain** = a DSS from the Harvard Medical School, to assist making a diagnosis (clinical consultation), and also as an instructional instrument (education); provides a description of diseases, etiology, pathology, prognosis and up to 10 references for each disease;
- **Expert-System** = emulates the decision making processes of a human expert to solve complex problems;
- **GAMUTS** in Radiology = Computer-Supported list of common/uncommon differential diagnoses;
- **ILIAD** = medical expert system, developed by the University of Utah, used as a teaching and testing tool for medical students in problem solving. Fields include Pediatrics, Internal Medicine, Oncology, Infectious Diseases, Gynecology, Pulmonology etc.
- **MYCIN** = one of the early medical expert systems (Shortliffe (1970), Stanford) to identify bacteria causing severe infections, such as bacteremia and meningitis, and to recommend antibiotics, with the dosage adjusted for patient's body weight;
- **Reasoning** = cognitive (thought) processes involved in making medical decisions (clinical reasoning, medical problem solving, diagnostic reasoning;

Learning Goals: At the end of this 8th lecture you …

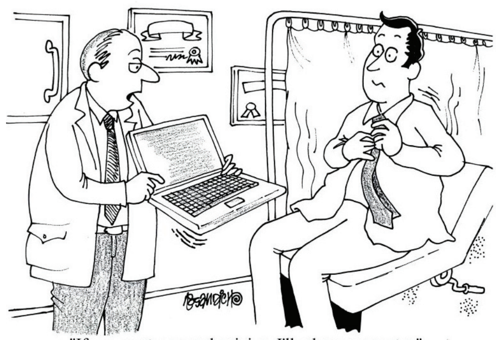
- … can apply your knowledge gained in lecture 7 to some example systems of decision support;
- … have an overview about the core principles and architecture of decision support systems;
- … are familiar with the certainty factors as e.g. used in MYCIN;
- … are aware of some design principles of DSS;
- … have seen similarities between DSS and KDD on the example of computational methods in cancer detection;
- … have seen basics of CBR systems;

Can Computers help doctors to make better decisions?

Slide 8-1 Key Challenges

- The development of medical expert systems is very difficult– as medicine is an extremely complex application domain – dealing most of the time probable information
- Some challenges include:
- (a) defining general system architectures in terms of generic tasks such as diagnosis, therapy planning and monitoring to be executed for (b) medical reasoning in (a);
- (c) patient management with (d) minimum uncertainty.
- Other challenges include: (e) knowledge acquisition and encoding, (f) human-computer interface and interaction; and (g) system integration into existing clinical environments, e.g. the enterprise hospital information system; to mention only a few.

Computers to help human doctors to make better decisions



"If you want a second opinion, I'll ask my computer."

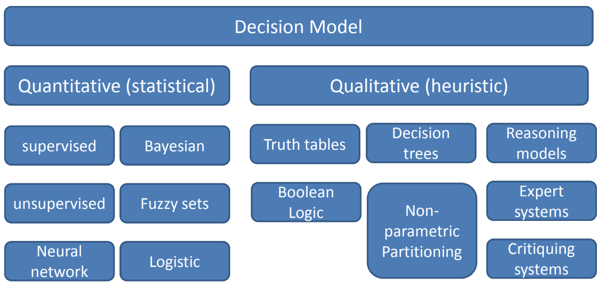
http://biomedicalcomputationreview.org/content/clinical-decision-support-providing-quality-healthcare-help-computer

Slide 8-2 Two types of decisions (Diagnosis vs. Therapy)

- **Type 1 Decisions:** <u>related to the **diagnosis**</u>, i.e. computers are used to assist in diagnosing a disease on the basis of the individual patient data. Questions include:
  - What is the probability that this patient has a myocardial infarction on the basis of given data (patient history, ECG, …)?
  - What is the probability that this patient has acute appendices, given the signs and symptoms concerning abdominal pain?
- **Type 2 Decisions:** <u>related to **therapy**</u>, i.e. computers are used to select the best therapy on the basis of clinical evidence, e.g.:
  - What is the best therapy for patients of age x and risks y, if an obstruction of more than z % is seen in the left coronary artery?
  - What amount of insulin should be prescribed for a patient during the next 5 days, given the blood sugar levels and the amount of insulin taken during the recent weeks?

Bemmel, J. H. V. & Musen, M. A. 1997. *Handbook of Medical Informatics, Heidelberg, Springer.*

Slide 8-3 Taxonomy of Decision Support Models

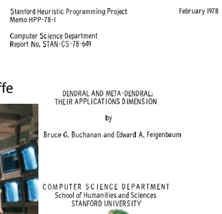


Bemmel, J. H. v. & Musen, M. A. (1997) *Handbook of Medical Informatics. Heidelberg, Springer.*

Where are the roots in Decision Support?

Slide 8-4 History of DSS is a history of artificial intelligence

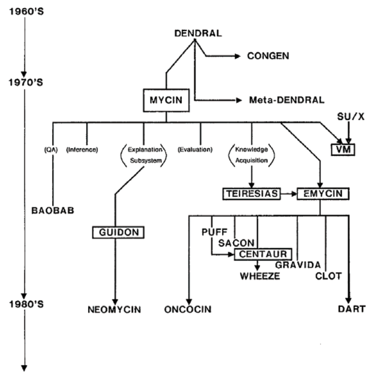
E. Feigenbaum, J. Lederberg, B. Buchanan, E. Shortliffe


Stanford Heuristic Programming Project
Memo HPP-78-1
February 1978
Computer Science Department
Report No. STAN-CS-78-649
DENDRAL AND META-DENDRAL: THEIR APPLICATIONS DIMENSION
by
Bruce G. Buchanan and Edward A. Feigenbaum
COMPUTER SCIENCE DEPARTMENT
School of Humanities and Sciences
STANFORD UNIVERSITY

Rheingold, H. (1985) *Tools for thought: the history and future of mind-expanding technology. New York, Simon & Schuster.*

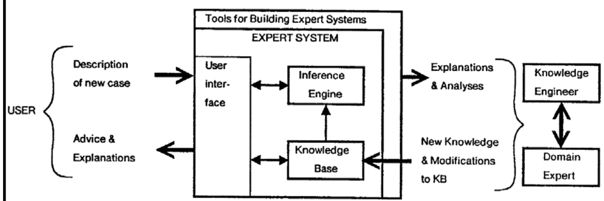
Buchanan, B. G. & Feigenbaum, E. A. (1978) DENDRAL and META-DENDRAL: their applications domain. *Artificial Intelligence, 11, 1978, 5-24.*

Slide 8-5 Evolution of Decision Support Systems



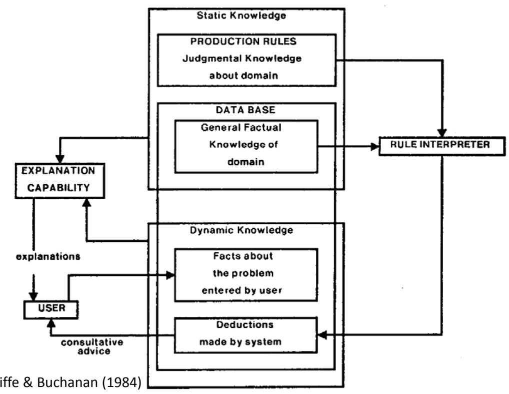
Shortliffe, E. H. & Buchanan, B. G. (1984) *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project. Addison-Wesley.*

Slide 8-6 Early Knowledge Based System Architecture



Shortliffe, T. & Davis, R. (1975) Some considerations for the implementation of knowledge-based expert systems *ACM SIGART Bulletin, 55, 9-12.*

Slide 8-7 Static Knowledge versus dynamic knowledge



Shortliffe & Buchanan (1984)

Slide 8-8 Dealing with uncertainty in the real world

- The information available to humans is often imperfect – imprecise - uncertain.
- This is especially in the medical domain the case.
- An **human agent** can cope with deficiencies.
- Classical logic permits only **exact reasoning**:
- IF A is true THEN A is non-false and
  IF B is false THEN B is non-true
- Most real-world problems do not provide this exact information, mostly it is inexact, incomplete, uncertain and/or **un-measurable!**

1967, Star Trek, I Mudd

Harcourt Fenton Mudd: Now listen, Spock, you may be a wonderful science officer but, believe me, you couldn't sell fake patents to your mother!

Spock: I fail to understand why I should care to induce my mother to purchase falsified patents.

Slide 8-9 MYCIN – rule based system - certainty factors

- MYCIN is a rule-based Expert System, which is used for therapy planning for patients with bacterial infections
- Goal oriented strategy ("Rückwärtsverkettung")
- To every rule and every entry a certainty factor (CF) is assigned, which is between 0 und 1
- Two measures are derived:
- MB: measure of belief
- MD: measure of disbelief
- Certainty factor – CF of an element is calculated by: $CF[h] = MB[h] - MD[h]$
- CF is positive, if more evidence is given for a hypothesis, otherwise CF is negative
- CF[h] = +1 -> h is 100 % true
- CF[h] = –1 -> h is 100% false

Slide 8-10 Original Example from MYCIN

h_1 = The identity of ORGANISM-1 is streptococcus
h_2 = PATIENT-1 is febrile
h_3 = The name of PATIENT-1 is John Jones

$CF[h_1,E] = .8$: There is strongly suggestive evidence (.8) that the identity of ORGANISM-1 is streptococcus

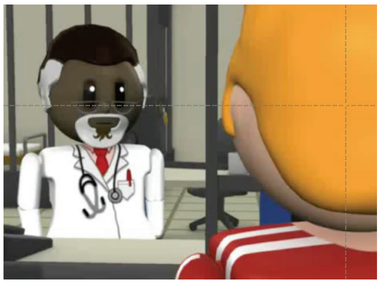
$CF[h_2,E] = -.3$: There is weakly suggestive evidence (.3) that PATIENT-1 is not febrile

$CF[h_3,E] = +1$: It is definite (1) that the name of PATIENT-1 is John Jones

Shortliffe, E. H. & Buchanan, B. G. (1984) *Rule-based expert systems: the MYCIN experiments of the Stanford Heuristic Programming Project. Addison-Wesley.*

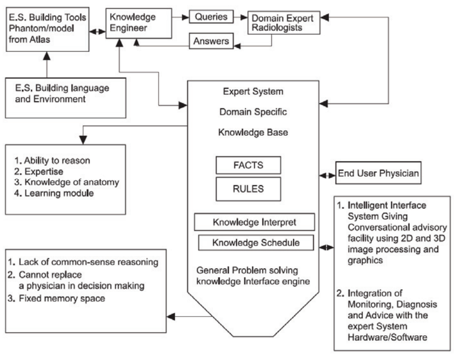
Slide 8-11 MYCIN was *no* success in the clinical practice

https://www.youtube.com/watch?v=IVGWM0CKNWA ("real nurse triage")



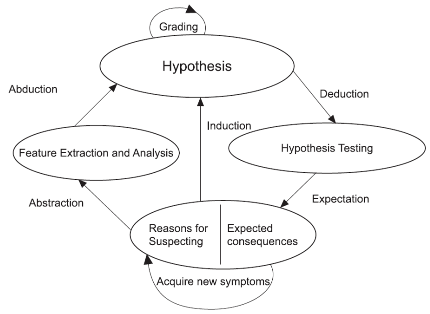
What challenges are in the development of DSS?

Slide 8-12 Basic Design Principles of a DSS



Majumder, D. D. & Bhattacharya, M. (2000) Cybernetic approach to medical technology: application to cancer screening and other diagnostics. Kybernetes, 29, 7/8, 871-895.

Slide 8-13 Cybernetic approach to medical diagnostics



Majumder, D. D. & Bhattacharya, M. (2000) Cybernetic approach to medical technology: application to cancer screening and other diagnostics. Kybernetes, 29, 7/8, 871-895.

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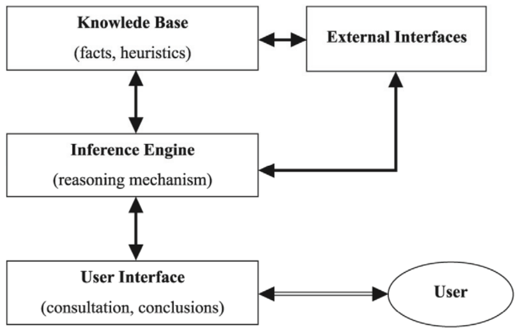
Slide 8-14 State-of-the-art architecture of DSS



Metaxiotis, K. & Psarras, J. (2003) Expert systems in business: applications and future directions for the operations researcher. *Industrial Management & Data Systems, 103, 5, 361-368.*

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Slide 8-15 On design and development of DSS

- Human–Computer cooperation is essential to the decision support process.
- Consequently, Human–Computer Interaction (HCI) is a fundamental aspect for building
- intelligent, interactive DSS,
- because the design of such systems heavily relies on a user-centered approach.
- It is necessary to combine and integrate methods from Software Engineering (SE) and HCI.
- Traditional methods and models are limited because the system is highly interactive and
- usually these methods do not integrate the end-user explicitly and systematically.

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How to combine SE and HCI for effective development of DSS?

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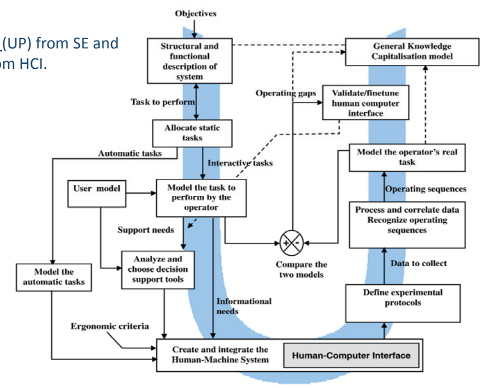
Slide 8-16 Example: Development following the U model 1/2

Unified Process (UP) from SE and the U-model from HCI.

Abed, M., Bernard, J. & Angué, J. (1991). *Task analysis and modelization by using SADT and Petri Networks. Tenth European Annual Conference on Human Decision Making and Manual Control, Liege, 11-13.*



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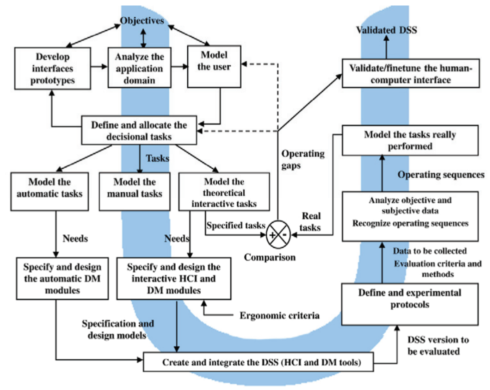
Slide 8-17 Improved U model 2/2

Ayed, B. M., Ltifi, H., Kolski, C. & Alimi, A. (2010) A user-centered approach for the design & implementatio of KDD-based DSS: A case study in the healthcare domain. *Decision Support Systems, 50, 64 78.*



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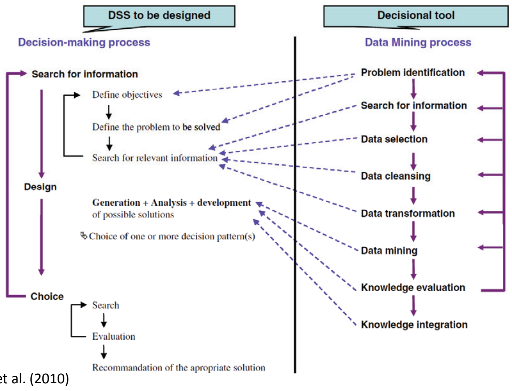
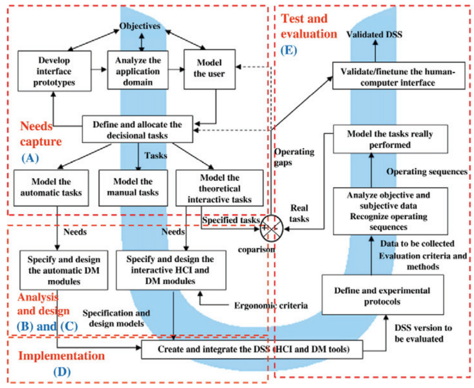
Slide 8-18 Remember the similarities between DSS and KDD



Ayed et al. (2010)

Slide 8-19 The Design Phases



Ayed et al. (2010)

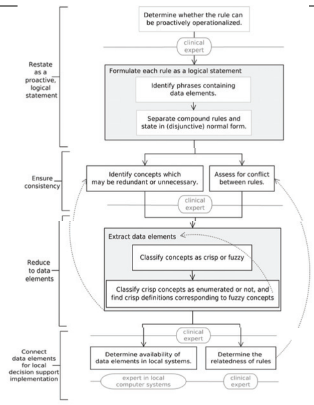
What is the simplest possibility of clinical decision support?

Slide 8-20 Clinical Guidelines as DSS & Quality Measure

- Clinical guidelines are **systematically** developed documents to assist doctors and patient decisions about appropriate care;
- In order to build DS, based on a guideline, it is **formalized** (transformed from natural language to a logical algorithm), and
- **implemented** (using the algorithm to program a DSS);
- To increase the quality of care, they must be linked to a process of care, for example:
  - "80% of diabetic patients should have an HbA1c below 7.0" could be linked to processes such as:
  - "All diabetic patients should have an annual HbA1c test" and
  - "Patients with values over 7.0 should be rechecked within 2 months."
- **Condition-action rules** specify one or a few conditions which are linked to a specific action, in contrast to narrative guidelines which describe a series of branching or iterative decisions unfolding over time.
- Narrative guidelines and clinical rules are two ends of a continuum of clinical care standards.

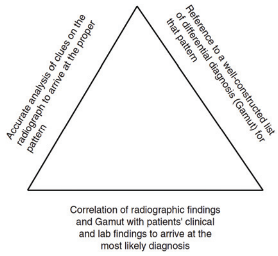
Slide 8-21 Clinical Guidelines

Medlock, S., Opondo, D., Eslami, S., Askari, M., Wierenga, P., de Rooij, S. E. & Abu-Hanna, A. (2011) LERM (Logical Elements Rule Method): A method for assessing and formalizing clinical rules for decision support. *International Journal of Medical Informatics, 80, 4, 286-295.*



Are there other possibilities for DS?

Slide 8-21b Gamuts: Triangulation to find diagnoses



Gamut F-137

PHRENIC NERVE PARALYSIS OR DYSFUNCTION

COMMON
1. Iatrogenic (eg, surgical injury; chest tube; therapeutic avulsion or injection; subclavian vein puncture)
2. Infection (eg, tuberculosis; fungus disease; abscess)
3. Neoplastic invasion or compression (esp. carcinoma of lung)

UNCOMMON
1. Aneurysm$_g$, aortic or other
2. Birth trauma (Erb's palsy)
3. Herpes zoster
4. Neuritis, peripheral (eg, diabetic neuropathy)
5. Neurologic disease$_g$ (eg, hemiplegia; encephalitis; polio; Guillain-Barré S.)
6. Pneumonia
7. Trauma

Reference
1. Prasad S, Athreya BH: Transient paralysis of the phrenic nerve associated with head injury. JAMA 1976;236:2532–2533

Reeder, M. M. & Felson, B. 2003. *Reeder and Felson's gamuts in radiology: comprehensive lists of roentgen differential diagnosis, New York, Springer Verlag.*

Slide -21c Example - Gamuts in Radiology

REEDER AND FELSON'S
GAMUTS IN RADIOLOGY

GAMUT G-25
EROSIVE GASTRITIS*

COMMON
1. Acute gastritis (eg, alcohol abuse)
2. Crohn's disease I I
3. Drugs (eg, aspirin I I; NSAID I; steroids)
4. *Helicobacter pylori* infection I
5. Idiopathic
6. [Normal areae gastricae I]
7. Peptic ulcer; hyperacidity

UNCOMMON
1. Corrosive gastritis I
2. *Cryptosporidium* antritis
3. [Lymphoma]
4. Opportunistic infection (eg, candidiasis {moniliasis} I; herpes simplex; cytomegalovirus)
5. Postoperative gastritis
6. Radiation therapy
7. Zollinger-Ellison S. I; multiple endocrine neoplasia (MEN) S.

* Superficial erosions or aphthoid ulcerations seen especially with double contrast technique.

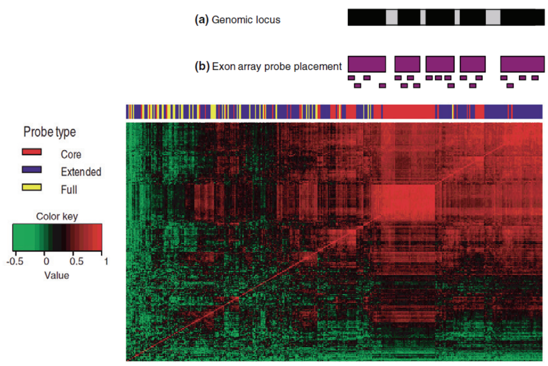
[ ] This condition does not actually cause the gamuted imaging finding, but can produce imaging changes that simulate it.

Reeder, M. M. & Felson, B. (2003) *Reeder and Felson's gamuts in radiology: comprehensive lists of roentgen differential diagnosis. New York, Springer Verlag.*

http://rfs.acr.org/gamuts/data/G-25.htm

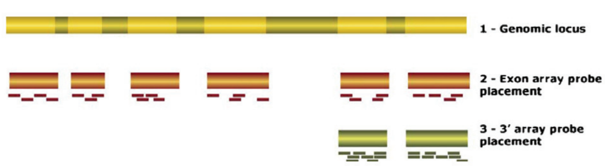
Towards Personalized Medicine

Slide 8-22 Example: Exon Arrays



Kapur, K., Xing, Y., Ouyang, Z. & Wong, W. (2007) Exon arrays provide accurate assessments of gene expression. *Genome Biology, 8, 5, R82.*

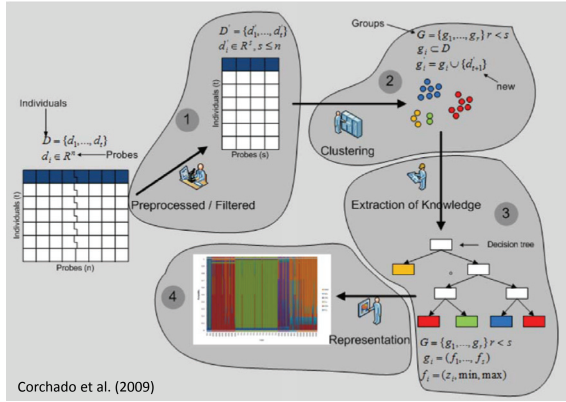
Slide 8-23 Computational leukemia cancer detection 1/6



Exon array structure. Probe design of exon arrays. (1) Exon—intron structure of a gene. Gray boxes represent introns, rest represent exons. Introns are not drawn to scale. (2) Probe design of exon arrays. Four probes target each putative exon. (3) Probe design of 30expression arrays. Probe target the 30end of mRNA sequence.

Corchado, J. M., De Paz, J. F., Rodriguez, S. & Bajo, J. (2009) Model of experts for decision support in the diagnosis of leukemia patients. *Artificial Intelligence in Medicine, 46, 3, 179-200.*

Slide 8-24 Computational leukemia cancer detection 2/6

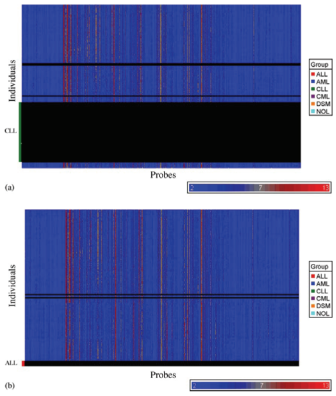


Corchado et al. (2009)

Slide 8-25 Computational leukemia cancer detection 3/6

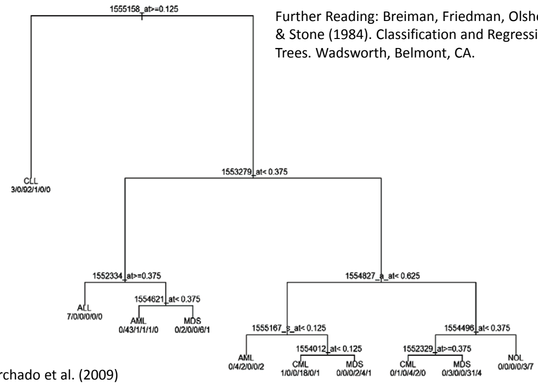
A = acute, C = chronic,
L = lymphocytic, M = myeloid

- **ALL** = cancer of the blood AND bone marrow caused by an abnormal proliferation of lymphocytes.
- **AML** = cancer in the bone marrow characterized by the proliferation of myeloblasts, red blood cells or abnormal platelets.
- **CLL** = cancer characterized by a proliferation of lymphocytes in the bone marrow.
- **CML** = caused by a proliferation of white blood cells in the bone marrow.
- **MDS** (Myelodysplastic Syndromes) = a group of diseases of the blood and bone marrow in which the bone marrow does not produce a sufficient amount of healthy cells.
- **NOL** (Normal) = No leukemias



Corchado et al. (2009)

8-26 Computational leukemia cancer detection 4/6

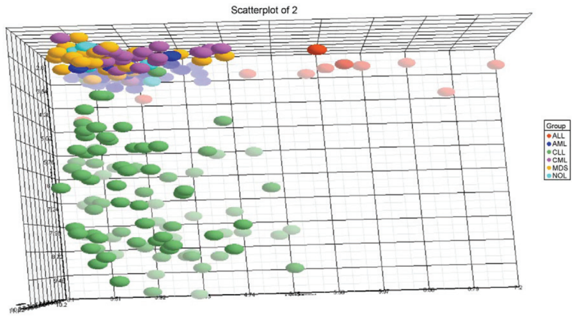


Further Reading: Breiman, Friedman, Olshen, & Stone (1984). Classification and Regression Trees. Wadsworth, Belmont, CA.

Corchado et al. (2009)

8-27 Computational leukemia cancer detection 5/6

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



Corchado et al. (2009)

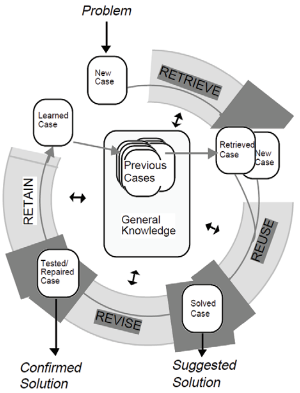
Slide 8-28 Computational leukemia cancer detection 6/6

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

What is Case-based reasoning?

Slide 8-29 Thinking – Reasoning – Deciding – Acting

Slide 8-30 Case Based Reasoning (CBR) Basic principle



Aamodt, A. & Plaza, E. (1994) Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI Communications, 7, 1, 39-59.*

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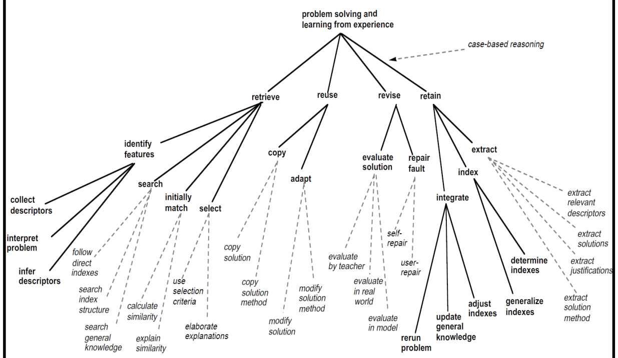
Slide 8-31 The task-method decomposition of CBR



Aamodt & Plaza (1994)

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Slide 8-32 CBR Example: Radiotherapy Planning 1/6

Source: http://www.teachingmedicalphysics.org.uk

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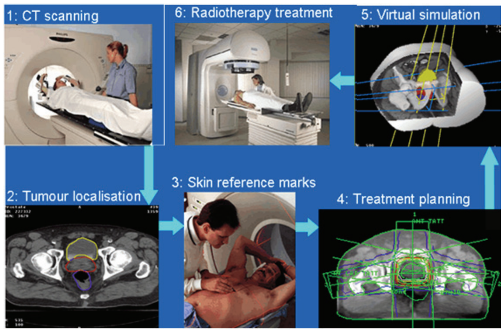
Slide 8-33 CBR Example: Radiotherapy Planning 2/6



Source: Imaging Performance Assessment of CT Scanners Group, http://www.impactscan.org

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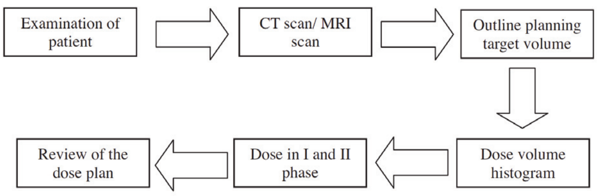
Slide 8-34 CBR Example: Radiotherapy Planning 3/6



Measures:

1) Clinical Stage = a labelling system
2) Gleason Score = grade of prostate cancer = integer between 1 to 10; and
3) Prostate Specific Antigen (PSA) value between 1 to 40
4) Dose Volume Histogram (DVH) = pot. risk to the rectum (66, 50, 25, 10 %)

Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

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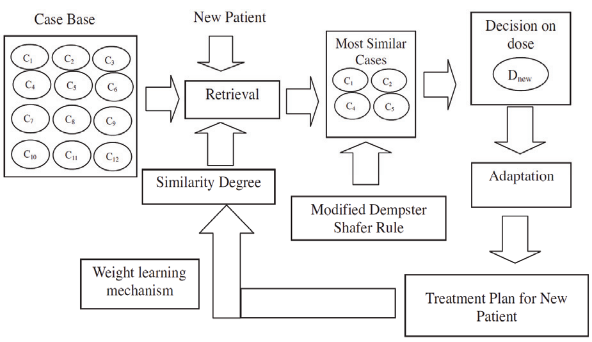
Slide 8-35 CBR System Architecture 4/6



Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

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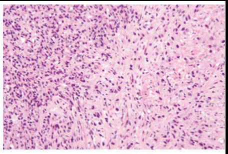
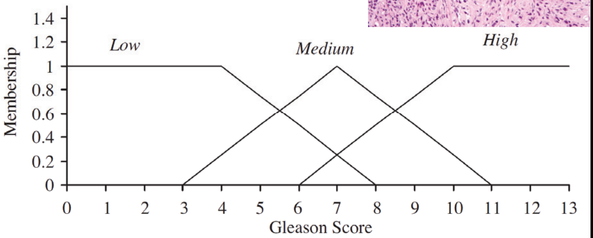
Slide 8-36 Membership funct. of fuzzy sets Gleason score 5/6

Gleason score evaluates the grade of prostate cancer. Values: integer within the range





Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

Slide 8-37 Case Based Reasoning 6/6

Petrovic et al. (2011)

Dose plan suggested by Dempster-Shafer rule (62Gy+10Gy}

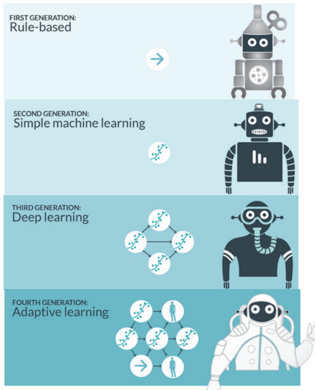
Dose received by 10% of rectum is 56.02 Gy (maximum dose limit =55 Gy)

Proposed dose plan ← Yes ← Feasible dose plan → No → Modification

Modification of dose plan:
New dose plan: 62Gy +8 Gy
Dose received by 10% of rectum is: 54.26 Gy (feasible dose plan)

Slide 8-38 Future Outlook from a technological perspective

"cognitive computing" "IBM Watson" "Deep Learning"



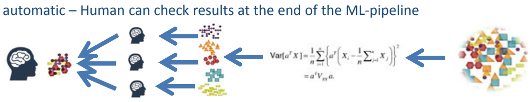
http://idibon.com

Slide 8-39 Future Outlook

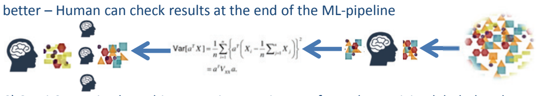
- Sometimes we do not have "big data", where aML-algorithms benefit.
- Sometimes we have
  - Small data
  - Rare Events
  - NP-hard problems (e.g. k-Anonymization, Protein-Folding, Graph Coloring, Subspace Clustering, …
- Then we still need the "human-in-the-loop"

HCI-KDD

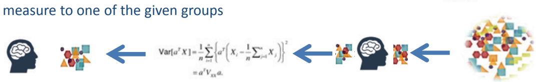
A) Unsupervised ML: Algorithm is applied on the raw data and learns fully automatic – Human can check results at the end of the ML-pipeline



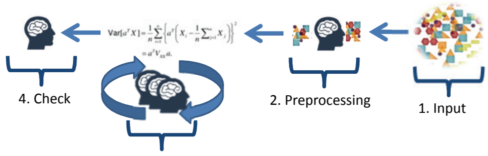
B) Supervised ML: Humans are providing the labels for the training data and/or select features to feed the algorithm to learn – the more samples the better – Human can check results at the end of the ML-pipeline



C) Semi-Supervised Machine Learning: A mixture of A and B – mixing labeled and unlabeled data so that the algorithm can find labels according to a similarity measure to one of the given groups



D) Interactive Machine Learning: Human is seen as an agent involved in the actual learning phase, step-by-step influencing measures like distance or cost functions …



Thank you!

Sample Questions

- What is human intelligence?
- What different decision models can be applied in medical informatics?
- How can we deal with uncertainty in the real world?
- What is the principle of a rule based expert system?
- Sketch the basic architecture of a DSS!
- Which basic design principles of a DSS must be considered?
- How does the U-model work?
- Which similarities exist between DSS and KDD?
- What are clinical guidelines?
- What is interesting in the computational method model of cancer detection of Corchado et al. (2009)?
- What is the basic principle of Case Based Reasoning?

Some Useful Links

- http://gaia.fdi.ucm.es/projects/jcolibri
- http://www-formal.stanford.edu/jmc/whatisai/whatisai.html
- http://aaai.org/AITopics
- http://www.stottlerhenke.com/ai_general/history.htm
- http://rfs.acr.org/gamuts (Gamuts in radiology - DSS for radiological imaging)
- http://www.scribd.com/doc/16093558/Gamuts-in-radiology (Reeder & Felsons Original Book on Gamuts)
- http://www.isradiology.org/gamuts/Gamuts.htm (Web-based Gamuts in Radiology)

3 July 1959, Volume 130, Number 3366 SCIENCE

Reasoning Foundations of Medical Diagnosis

Symbolic logic, probability, and value theory aid our understanding of how physicians reason.

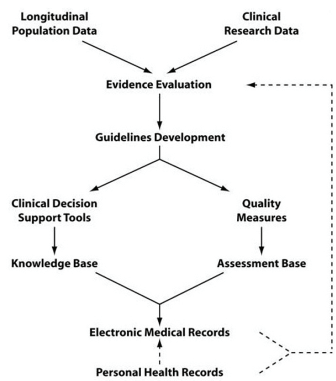
Robert S. Ledley and Lee B. Lusted

The purpose of this article is to analyze the complicated reasoning processes inherent in medical diagnosis. The importance of this problem has received recent emphasis by the increasing interest in the use of electronic computers as an aid to medical diagnostic processes … fitted into a definite disease category, or that it may be one of several possible diseases, or else that its exact nature cannot be determined." This, obviously, is a greatly simplified explanation of the process of diagnosis, for the physician might also comment that after seeing a … ance are the ones who do remember and consider the most possibilities."

Computers are especially suited to help the physician collect and process clinical information and remind him of diagnoses which he may have overlooked. In many cases computers may be as simple as a set of hand-sorted cards, whereas in other cases the use of a large-scale digital electronic computer may be indicated. There are other ways in which computers may serve the physician, and some of these are suggested in this paper. For example, medical students might find the computer an important aid in learning the methods of differential diagnosis. But to use the computer thus we must understand how the physician makes a medical diagnosis. This, then, brings us to the subject of our investigation: the reasoning foundations of medical diagnosis and treatment.

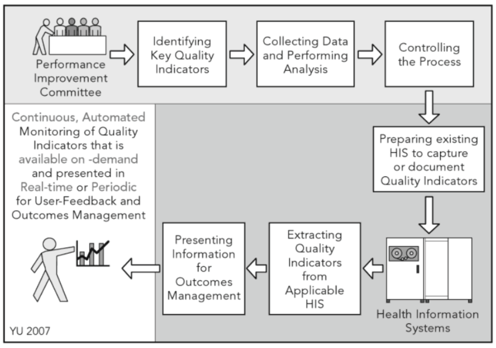
Medical diagnosis involves processes that can be systematically analyzed, as well as those characterized as "intangible." For instance, the reasoning foundations of medical diagnostic procedures

Appendix: CDS Tools and EHR for quality measures



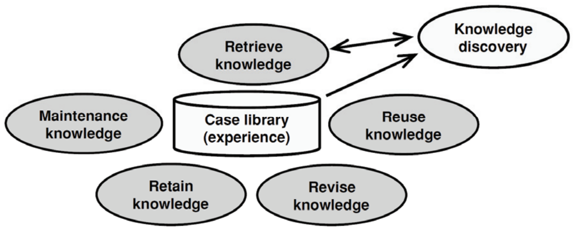
Downing, G., Boyle, S., Brinner, K. & Osheroff, J. (2009) Information management to enable personalized medicine: stakeholder roles in building clinical decision support. *BMC Medical Informatics and Decision Making, 9, 1, 1-11.*

Appendix: Quality Improvement and Health Records



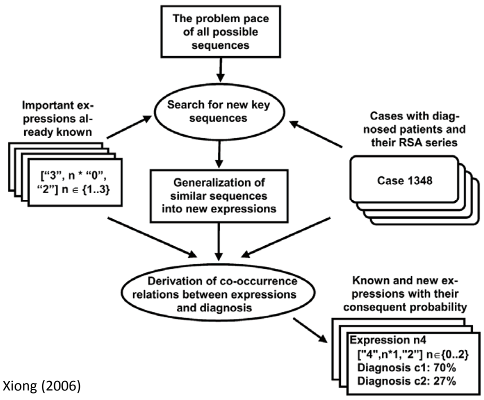
Yu, F.B., Allison, J.J., Houston T.K. (2008) Quality Improvement & the Electronic Health Record: Concepts and Methods. In: Carter, J. H. (2008) *Electronic health records: a guide for clinicians & administrators. ACP Press.*

Appendix: Example for a Knowledge discovery module



Funk, P. & Xiong, N. (2006) Case-based reasoning and knowledge discovery in medical applications with time series. *Computational Intelligence, 22, 3-4, 238-253.*

Appendix: Discovery of new expressions & co-occurrences



Funk & Xiong (2006)

Appendix: Evaluation of a Sequence

Given a sequence *s* there may be a set of probable consequent classes *{C1, C2, . . . ,Ck}*

The strength of the co-occurrence between sequence *s* and class *Ci* (*i* = 1, . . . , *k*) can be measured by the probability, *p*(*Ci* | *s*), of *Ci* conditioned upon *s*

$$PD(s) = \max_{i=1\cdots k} P(C_i \mid s) \qquad P(C_i \mid s) = \frac{P(s \mid C_i)P(C_i)}{P(s)}$$

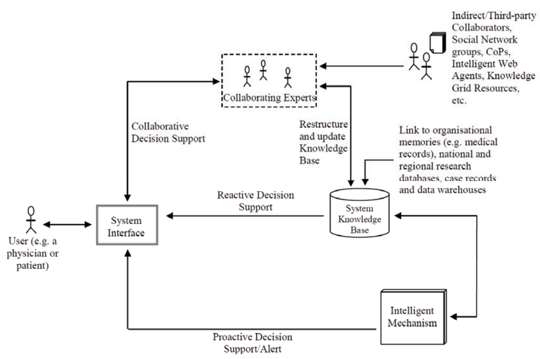
$$P(s) = P(s \mid C_i)P(C_i) + P(s \mid \bar{C}_i)P(\bar{C}_i)$$

$$P(C_i \mid s) = \frac{P(s \mid C_i)P(C_i)}{P(s \mid C_i)P(C_i) + P(s \mid \bar{C}_i)P(\bar{C}_i)}$$

$$P(C_i \mid s) \approx \frac{N(C_i, s)}{N(s)}$$

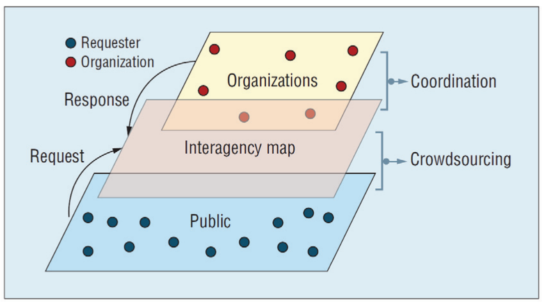
Funk & Xiong (2006)

Appendix: Example for Interactive Group Decision Support



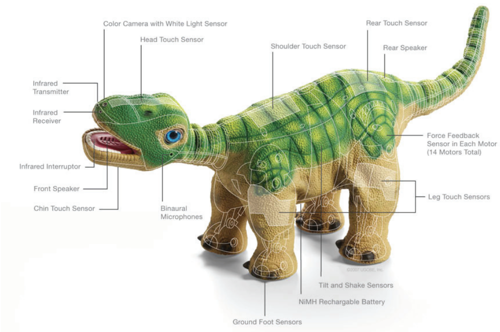
Anya, O., Tawfik, H. & Nagar, A. (2011) Cross-boundary knowledge-based decision support in e-health. *International Conference on Innovations in Information Technology (IIT). 150-155.*

Appendix: Crowdsourcing - Example Disaster Management

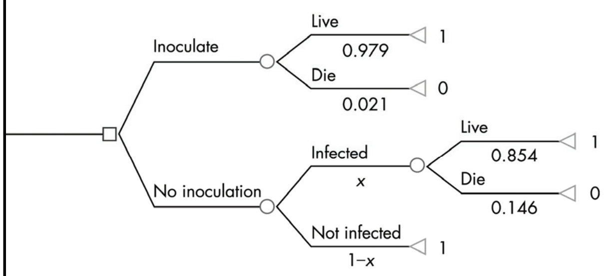


Gao, H., Barbier, G. & Goolsby, R. (2011) Harnessing the Crowdsourcing Power of Social Media for Disaster Relief. *Intelligent Systems, IEEE, 26, 3, 10-14.*

Example: Pleo robot - Intelligent behaviour?

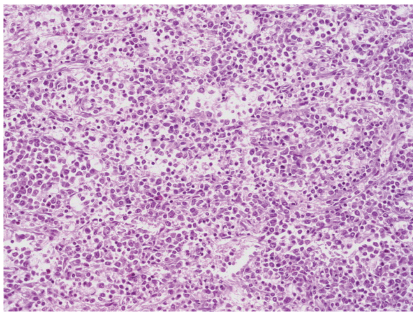


Clinical Decision Tree (CDT) is still state-of-the-art



Ferrando, A., Pagano, E., Scaglione, L., Petrinco, M., Gregori, D. & Ciccone, G. (2009) A decision-tree model to estimate the impact on cost-effectiveness of a venous thromboembolism prophylaxis guideline. *Quality and Safety in Health Care, 18, 4, 309-313.*

Example (Part B): Leukemia



This 79 y/o female with chronic myeloid leukemia presented with rapidly enlarging spleen. The splenectomy specimen showed a dark red surface devoid of white pulp. Majority of the large tumor cells seen here were positive for CD34. This is a case of chronic myeloid leukemia in **blast transformation (Richter's Syndrome)** Source: webpathology.com