Mini Course

From Data Science to interpretable AI

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Day 1 > Part 3 > Monday, 17.06.2019

Decision Making and Decision Support

Note

This is the version for printing and reading. The lecture version is didactically different.

Overview

Day 1 - Fundamentals

01 Introduction to AI
Machine Learning

02 Data, Information and Knowledge

03 Decision Making and Decision Support

04 Causal Reasoning and Interpretable AI

Keywords (1/2)

- Decision support system (DSS)
- MYCIN – Rule Based Expert System
- GAMUTS in Radiology
- Reasoning under uncertainty
- Example: Radiotherapy planning
- Example: Case-Based Reasoning
- Explainable Artificial intelligence
- Re-trace > Understand > Explain
- Transparency > Trust > Acceptance
- Fairness > Transparency > Accountability
- Causality > Causability

Keywords (2/2)

- Decision
- Cognition
- Intelligence
- Expected Utility Theory
- Probabilistic Inference
- Probabilistic Decision Theory
- Signal Detection Theory
- ROC curve
- Learning and Inference
- Naïve Bayes Classifier

Advance Organizer (1/4)

- **Argmax/argmin** = set of points for which f(x) attains the function's largest/smallest value.
- **Brute Force** = systematically computing all possible candidates for a solution and checking whether each candidate satisfies the problem's statement;
- **Cognition** = mental processes of gaining knowledge, comprehension, including thinking, attention, remembering, language understanding, decision making and problem-solving;
- **Cognitive Science** = interdisciplinary study of human information processing, including perception, language, memory, reasoning, and emotion;
- **Confounding Variable** = an unforeseen, unwanted variable that jeopardizes reliability and validity of a study outcome.
- **Correlation coefficient** = measures the relationship between pairs of interval variables in a sample, from r = -1.00 to 0 (no correlation) to r = +1.00
- **Decision Making** = a central cognitive process in every medical activity, resulting in the selection of a final choice of action out of alternatives; according to Shortliffe (2011) DM is still the key topic in medical informatics;
- **Diagnosis** = classification of a patient's condition into separate and distinct categories that allow medical decisions about treatment and prognostic;
- **Differential Diagnosis (DDx)** = a systematic method to identify the presence of an entity where multiple alternatives are possible, and the process of elimination, or interpretation of the probabilities of conditions to negligible levels;
- **Evidence-based medicine (EBM)** = aiming at the best available evidence gained from the scientific method to clinical decision making. It seeks to assess the strength of evidence of the risks and benefits of treatments (including lack of treatment) and diagnostic tests. Evidence quality can range from meta-analyses and systematic reviews of double-blind, placebo-controlled clinical trials at the top end, down to conventional wisdom at the bottom; NOTE: Evidence (English) is NOT Evidenz (Deutsch)!
- **Expected Utility Theory (EUT)** = states that the decision maker selects between risky or uncertain prospects by comparing their expected utility values.

Advance Organizer (2/4)

- **External Validity** = the extent to which the results of a study are generalizable or transferable;
- **Hypothetico-Deductive Model (HDM)** = formulating a hypothesis in a form that could conceivably be falsified by a test on observable data, e.g. a test which shows results contrary to the prediction of the hypothesis is the falsification, a test that could but is not contrary to the hypothesis corroborates the theory – then you need to compare the explanatory value of competing hypotheses by testing how strong they are supported by their predictions;
- **Internal Validity** = the rigor with which a study was conducted (e.g., the design, the care taken to conduct measurements, and decisions concerning what was and was not measured);
- **PDCA** = Plan-Do-Check-Act, The so called PDCA-cycle or Deming-wheel can be used to coordinate a systematic and continuous improvement. Every improvement starts with a goal and with a plan on how to achieve that goal, followed by action, measurement and comparison of the gained output.
- **Perception** = sensory experience of the world, involving the recognition of environmental stimuli and actions in response to these stimuli;
- **Qualitative Research** = empirical research exploring relationships using textual, rather than quantitative data, e.g. case study, observation, ethnography; Results are not considered generalizable, but sometimes at least transferable.
- **Quantitative Research** = empirical research exploring relationships using numeric data, e.g. surveys, quasi-experiments, experiments. Results should be generalized, although it is not always possible.
- **Reasoning** = cognitive (thought) processes involved in making medical decisions (clinical reasoning, medical problem solving, diagnostic reasoning, behind every action;
- **Receiver-operating characteristic (ROC)** = in signal detection theory this is a graphical plot of the sensitivity, or true positive rate, vs. false positive rate (1 − specificity or 1 − true negative rate), for a binary classifier system as its discrimination threshold is varied;
- **Symbolic reasoning** = logical deduction
- **Triage** = process of judging the priority of patients' treatments based on the severity of their condition;

Advance Organizer (3/4)

- **Causality** = fundamental relationship between cause and effect
- Causability = similar to the concept of usability the property of a human explanation
- **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;
- Counterfactual = relating to or expressing what has not happened or is not the case
- **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;
- **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;

Advance Organizer (4/4)

- **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;
- Etiology = in medicine (many) factors coming together to cause an illness (see causality)
- Explainable AI = Explainability = upcoming fundamental topic within recent AI; answering e.g. **why** a decision has been made
- **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.
- Interpretability = there is no formal technical definition yet, but it is considered as a prerequisite for trust
- **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;
- **Transparency** = opposite of opacity of black-box approaches, and connotes the ability to understand how a model works (that does not mean that it should always be understood, but that – in the case of necessity – it can be re-enacted

Abbreviations

- CES = Central Executive System
- DDx = Differential Diagnosis
- DM = Decision Making
- DSS = Decision Support System
- EBM = Evidence-based medicine
- fMRI = functional Magnetic Resonance Image
- HDM = Hypothetico-Deductive Model
- IOM = Institute of Medicine
- LTS = Long Term Storage
- ME = Medical Error
- PDCA = Plan-Do-Check-Act
- QM = Quality Management
- ROC = Receiver Operating Characteristic
- RST = Rough Set Theory
- STS = Short Term Storage
- USTS = Ultra Short Term Storage (Sensory Register)

Learning Goals: At the end of this lecture you …

- … can apply your knowledge gained in the previous lectures to 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;

Reflection from last lecture

1

2

$C_1 \sqcup \ldots \sqcup C_n$

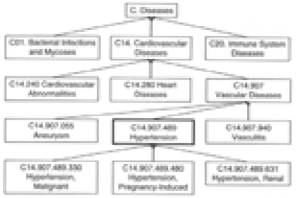
3

4

A
24184005|Finding of increased blood pressure (finding)| →
389360003|Abnormal blood pressure (finding)| AND
roleGroup SOME
(363714003|Interprets (attribute)| SOME
75367002|Blood pressure (observable entity|))

B
12763006|Finding of decreased blood pressure (finding)| →
392570002|Blood pressure finding (finding)| AND
roleGroup SOME
(363714003|Interprets (attribute)| SOME
75367002|Blood pressure (observable entity|))

5



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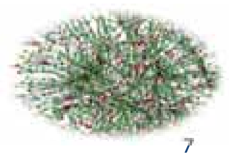

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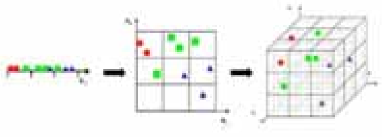

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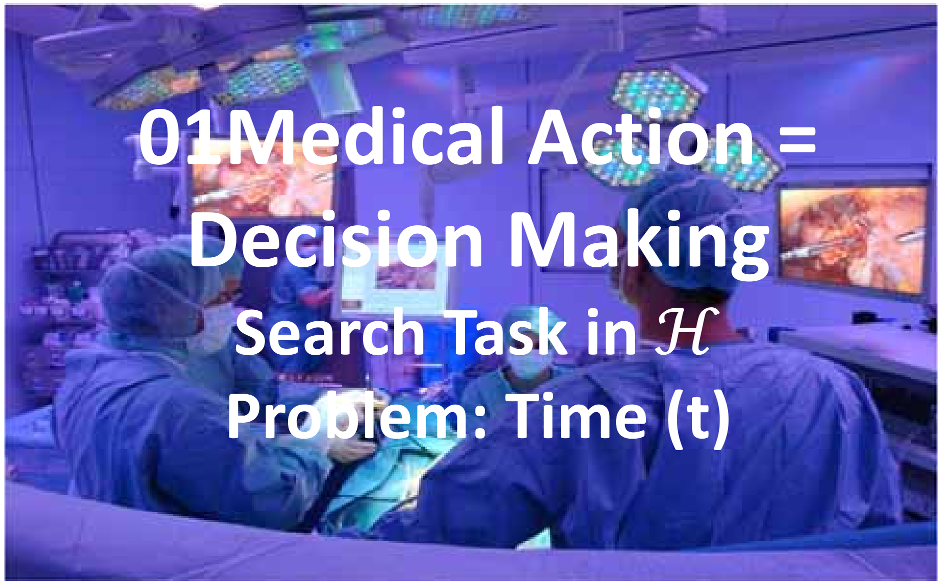
Key Challenges

- Medicine is an extremely complex application domain – dealing most of the time with uncertainties -> **probable information!**
- Key: Structure learning and prediction in large-scale biomedical networks with **probabilistic graphical models**
- Causality and Probabilistic Inference:
- Uncertainties are present at all levels in health related systems
- Data sets are noisy, mislabeled, atypical, dirty, wrong, etc. etc.
- Even with data of high quality from different real-world sources requires **processing uncertain information to make viable decisions.**
- In the increasingly complicated settings of modern science, model structure or **causal relationships may not be known a-priori** [1].
- Approximating probabilistic inference in Bayesian belief networks is NP-hard [2] -> here we need the "human-in-the-loop" [3]

[1] Sun, X., Janzing, D. & Schölkopf, B. Causal Inference by Choosing Graphs with Most Plausible Markov Kernels. ISAIM, 2006.
[2] Dagum, P. & Luby, M. 1993. Approximating probabilistic inference in Bayesian belief networks is NP-hard. Artificial intelligence, 60, (1), 141-153.
[3] Holzinger, A. 2016. Interactive Machine Learning for Health Informatics: When do we need the human-in-the-loop? Springer Brain Informatics (BRIN), 3, 1-13, doi:10.1007/s40708-016-0042-6.



Search in an arbitrarily high-dimensional space < 5 min.!

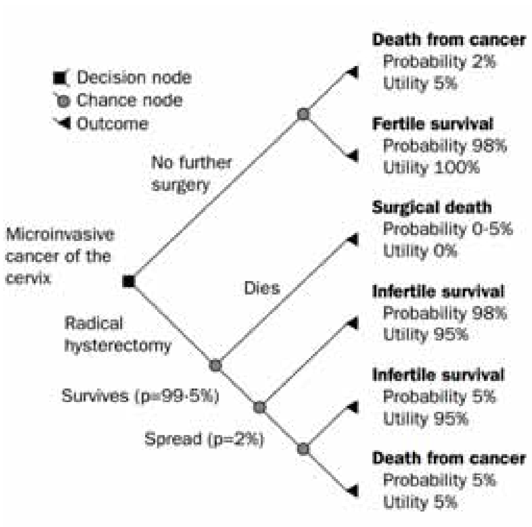
Decision Making is central in any (medical) work

Source: Cisco (2008). Cisco Health Presence Trial at Aberdeen Royal Infirmary in Scotland

The Medical Domain and Decision Making

- 400 BC Hippocrates (460-370 BC), father of western medicine:
  - A medical record should accurately reflect the course of a disease
  - A medical record should indicate the probable cause of a disease
- **1890** William Osler (1849-1919), father of modern western medicine
  - **Medicine is a science of uncertainty and an art of probabilistic decision making**
- Today
  - Prediction models are based on data features, patient health status is modelled as high-dimensional feature vectors …

Decision trees are coming from Clinical Practice



Physician treating a patient approx. 480 B.C.
Beazley (1963), Attic Red-figured Vase-Painters, 813, 96.
Department of Greek, Etruscan and Roman Antiquities, Sully, 1st floor, Campana Gallery, room 43 Louvre, Paris

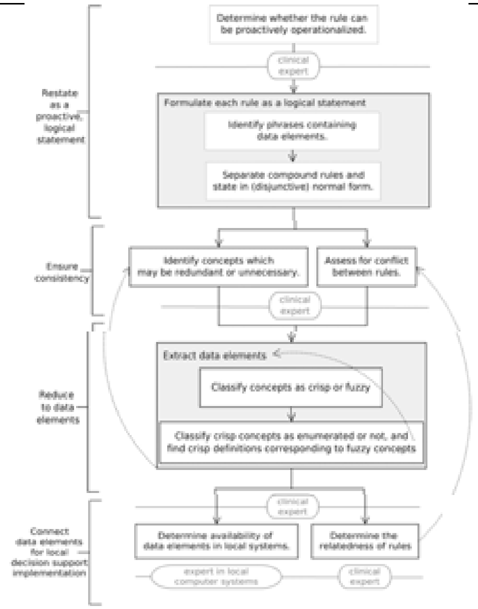
Elwyn, G., Edwards, A., Eccles, M. & Rovner, D. 2001. Decision analysis in patient care. The Lancet, 358, (9281), 571-574.

Clinical Guidelines as DSS & Quality Measure

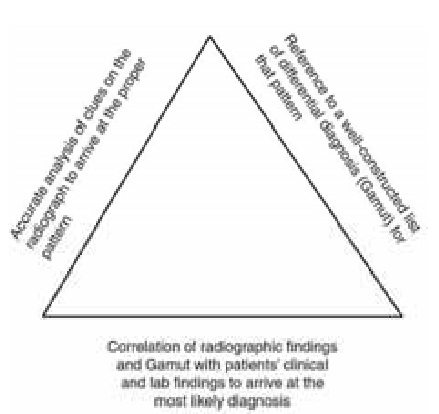
- Clinical guidelines are **systematically** developed documents to assist doctors and patient decisions about appropriate care;
- In order to build DS, based on a guideline, it is **formalized** (transformed from natural language to a logical algorithm), and
- **implemented** (using the algorithm to 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.

Example: 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.*



Example: Triangulation to find diagnoses



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


Gamut F-137

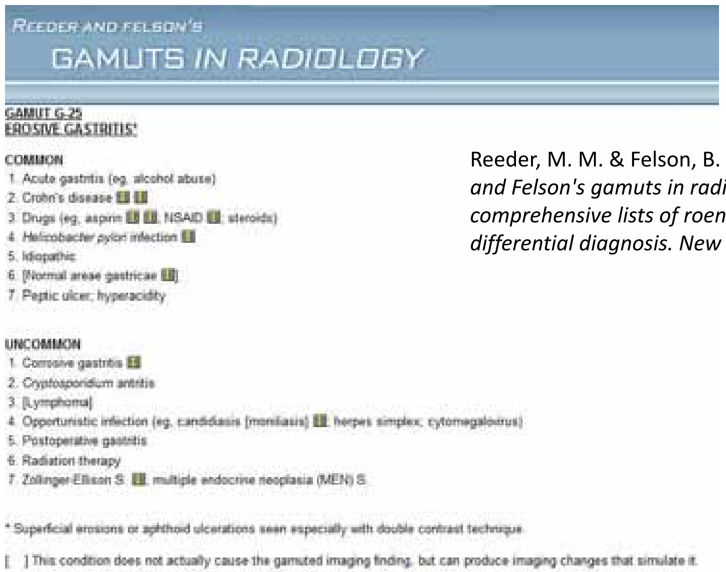
PHRENIC NERVE PARALYSIS OR DYSFUNCTION

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, aortic or other
2. Birth trauma (Erb's palsy)
3. Herpes zoster
4. Neuritis, peripheral (eg, diabetic neuropathy)
5. Neurologic disease (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

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
3. Drugs (eg, aspirin; NSAID; steroids)
4. Helicobacter pylori infection
5. Idiopathic
6. [Normal areae gastricae]
7. Peptic ulcer; hyperacidity

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

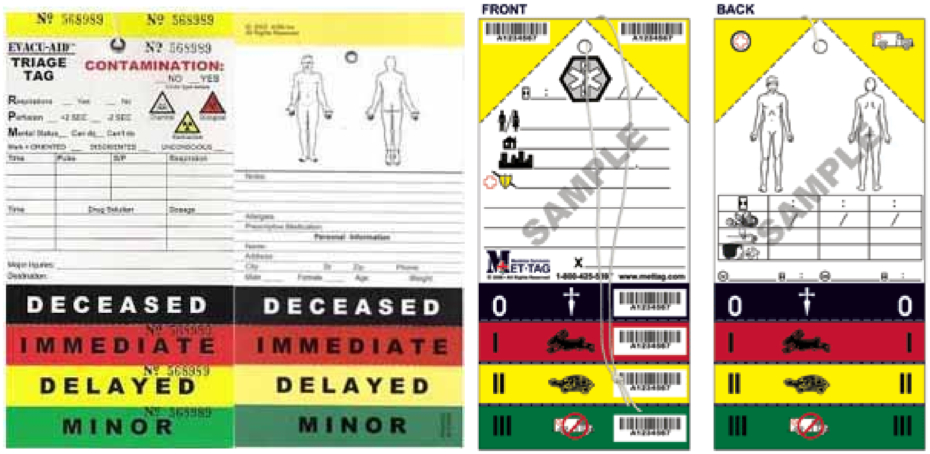
* Superficial erosions or aphthoid ulcerations seen especially with double contrast technique

[ ] 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*

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

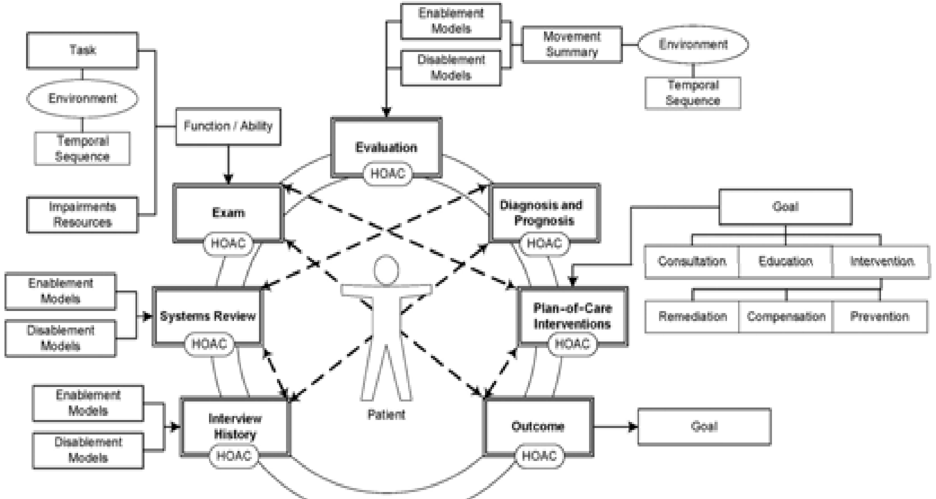
Example: Triage Tags - International Triage Tags



Iserson, K. V. & Moskop, J. C. 2007. Triage in Medicine, Part I: Concept, History, and Types. Annals of Emergency Medicine, 49, (3), 275-281.

Image Source: http://store.gomed-tech.com

Example Clinical DSS: Hypothesis-Oriented Algorithm



HOAC =Hypothesis-Oriented Algorithm for Clinicians

Schenkman, M., Deutsch, J. E. & Gill-Body, K. M. (2006) An Integrated Framework for Decision Making in Neurologic Physical Therapist Practice. *Physical Therapy, 86, 12, 1681-1702.*

Example Prediction Models > Feature Generation

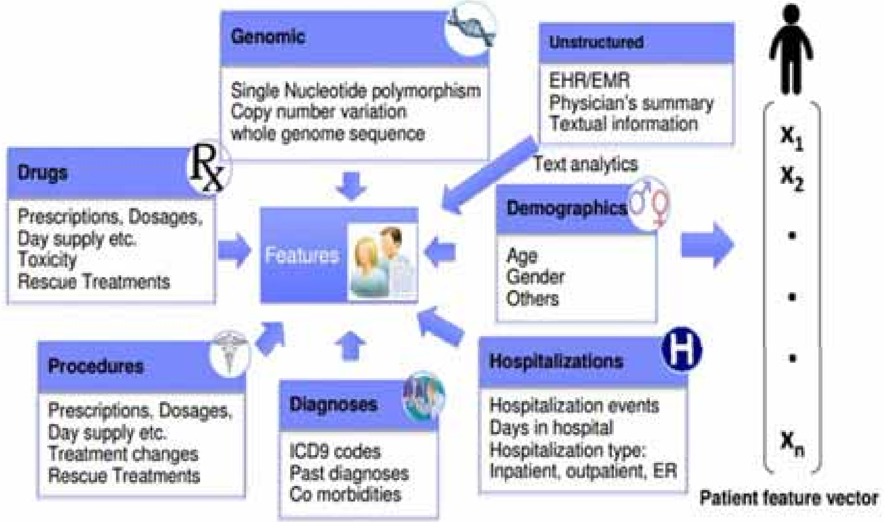


Image credit to Michal Rosen-Zvi

02 Can AI help doctors to make better decisions?

Computers to help human doctors to make better decisions

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

Augmenting Human Capabilities …

Two types of decisions (Diagnosis vs. Therapy)

- **Type 1 Decisions:** related to the **diagnosis,** 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:** related to **therapy,** 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?

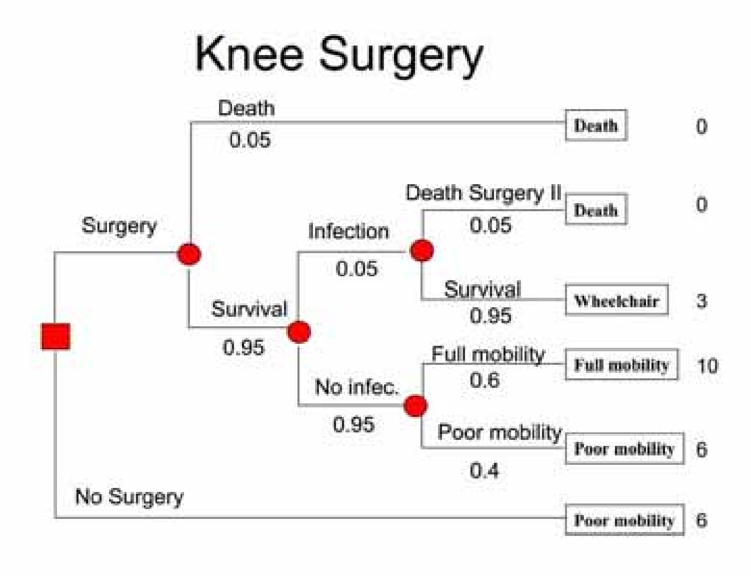
Bemmel, J. H. V. & Musen, M. A. 1997. *Handbook of Medical Informatics, Heidelberg, Springer.*

Example: Knee Surgery of a Soccer Player

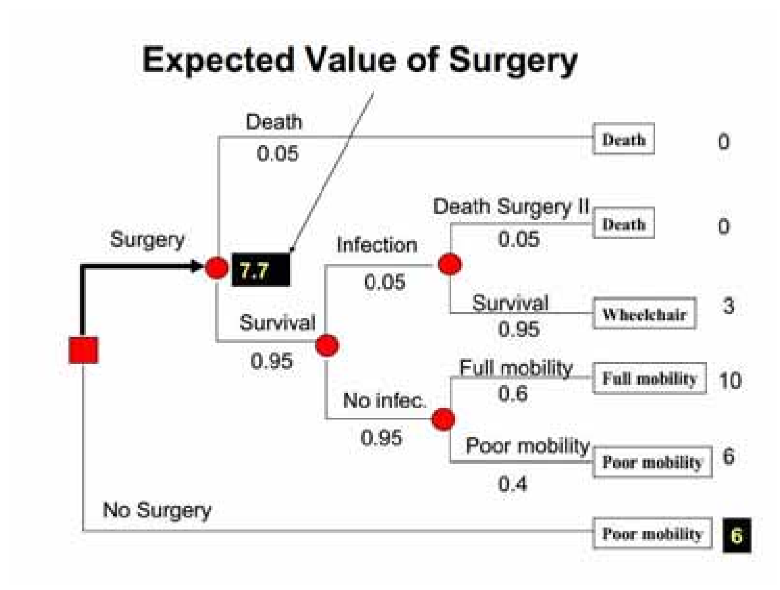
- Example of a Decision Problem
- Soccer player considering knee surgery
- Uncertainties:
- Success: recovering full mobility
- Risks: infection in surgery (if so, needs another surgery and may loose more mobility)
- Survival chances of surgery

Harvard-MIT Division of Health Sciences and Technology
HST.951J: Medical Decision Support, Fall 2005
Instructors: Professor Lucila Ohno-Machado and Professor Staal Vinterbo

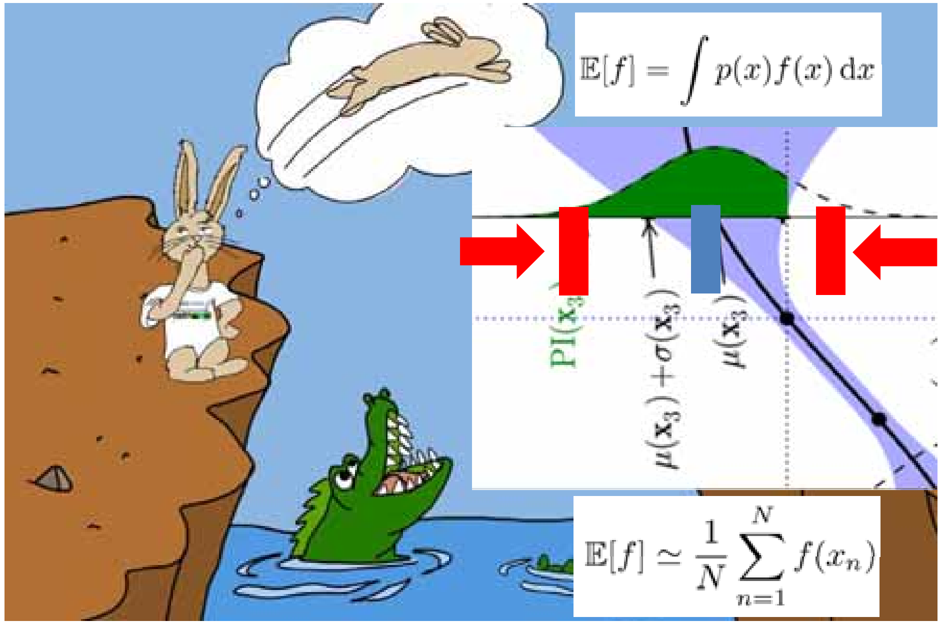
Decision Tree (this is known since Hippocrates!)



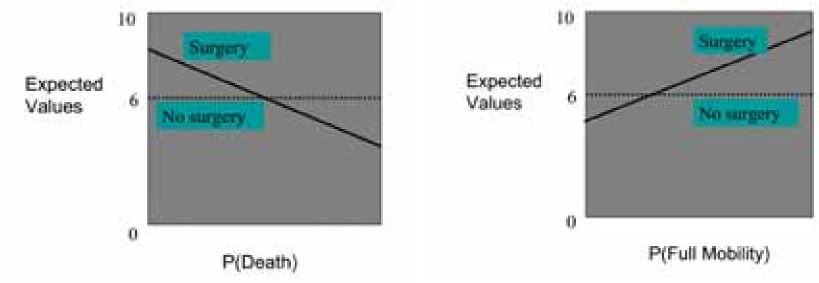
Helps to make rational decisions (risks vs. success)



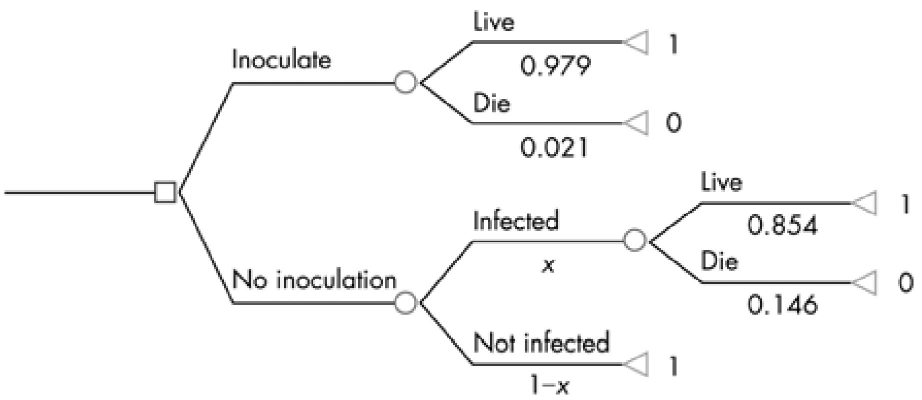
Estimate Confidence Interval: Uncertainty matters !



Effect of probabilities in the decision



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.*

Remember: Expected Utility Theory $E\ (U|d)$

For a single decision variable an agent can select $D = d$ for any $d \in dom(D)$.
The expected utility of decision $D = d$ is

http://www.eoht.info/page/Oskar+Morgenstern

$$E(U \mid d) = \sum_{x_1,\ldots,x_n} P(x_1,\ldots,x_n \mid d) U(x_1,\ldots,x_n,d)$$

An optimal single decision is the decision $D = dmax$ whose expected utility is maximal:

$$d_{\max} = \arg \max_{d \in \mathrm{dom}(D)} E(U \mid d)$$

Von Neumann, J. & Morgenstern, O. 1947. Theory of games and economic behavior, Princeton university press.

Taxonomy of Decision Support Models

Decision Model

- Quantitative (statistical)
  - supervised
  - Bayesian
  - unsupervised
  - Fuzzy sets
  - Neural network
  - Logistic
- Qualitative (heuristic)
  - Truth tables
  - Decision trees
  - Reasoning models
  - Boolean Logic
  - Non-parametric Partitioning
  - Expert systems
  - Critiquing systems

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

03 History of DSS = History of AI

A ultrashort history of Early AI

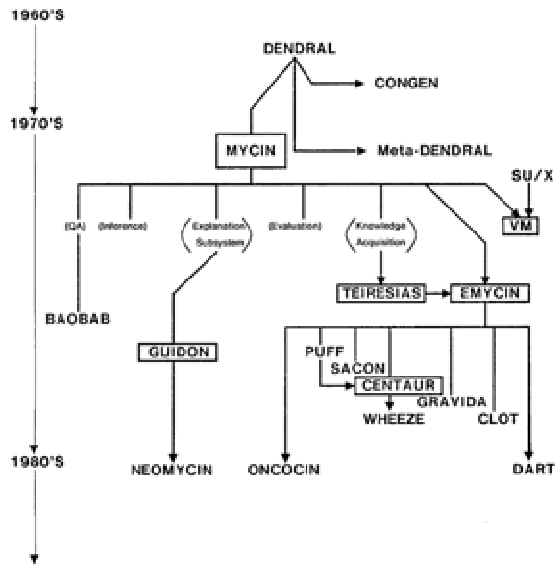
- **1943** McCulloch, W.S. & Pitts, W. A logical calculus of the ideas immanent in nervous activity. Bulletin of Mathematical Biology, 5, (4), 115-133, doi:10.1007/BF02459570.
- **1950** Turing, A.M. Computing machinery and intelligence. Mind, 59, (236), 433-460.
- 1958 John McCarthy Advice Taker: programs with common sense
- **1959** Samuel, A.L. Some studies in machine learning using the game of checkers. IBM Journal of research and development, 3, (3), 210-229, doi:10.1147/rd.33.0210.
- **1975** Shortliffe, E.H. & Buchanan, B.G. 1975. A model of inexact reasoning in medicine. Mathematical biosciences, 23, (3-4), 351-379, doi:10.1016/0025-5564(75)90047-4.
- 1978 Bellman, R. Can Computers Think? Automation of Thinking, problem solving, decision-making …

Five decades of Health Informatics

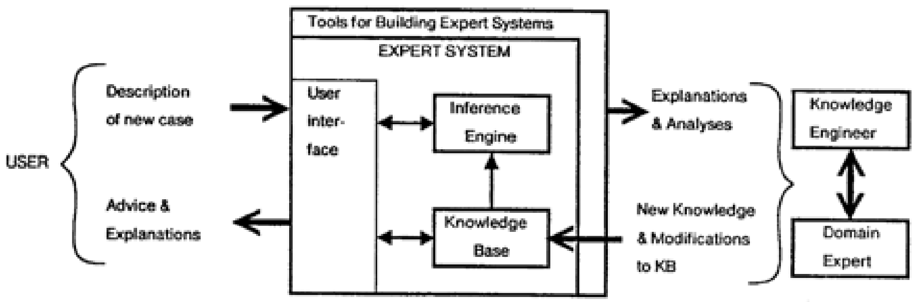
- 1960+ Medical Informatics (AI Hype)
  - Focus on data acquisition, storage, accounting (typ. “EDV”), Expert Systems
  - The term was first used in 1968 and the first course was set up 1978 !
- 1985+ Health Telematics (AI winter)
  - Health care networks, Telemedicine, CPOE-Systems, …
- 1995+ Web Era (AI is “forgotten”)
  - Web based applications, Services, EPR, distributed systems, …
- 2005+ Success statistical learning (AI renaissance)
  - Pervasive, ubiquitous Computing, Internet of things, …
- 2010+ Data Era – Big Data (super for AI)
  - Massive increase of data – data integration, mapping, …
- 2020+ Information Era – (towards explainable AI)
  - Sensemaking, disentangling the underlying concepts, **causality,** …

Evolution of Decision Support Systems (Expert Systems)

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

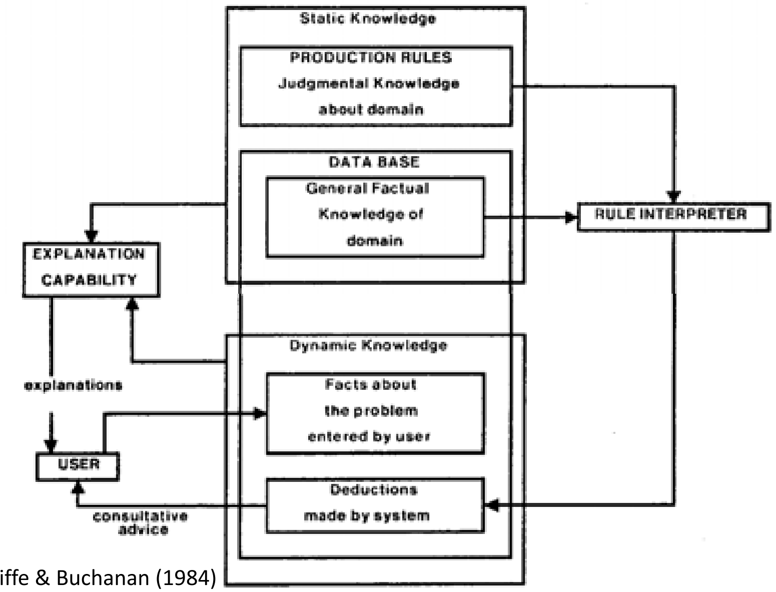


Early Knowledge Based System Architecture



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

Static Knowledge versus dynamic knowledge



Shortliffe & Buchanan (1984)

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!**

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

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.*

MYCIN was *no* success in the clinical routine

However, AI was extremely popular in the 1970ies


4.

Die Geheimnisse des Rechenautomaten

Image credit to Bernhard Schölkopf

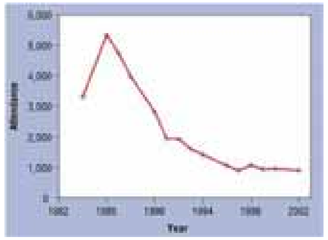
Cybernetics was praised as the solution for everything

Image credit to Bernhard Schölkopf

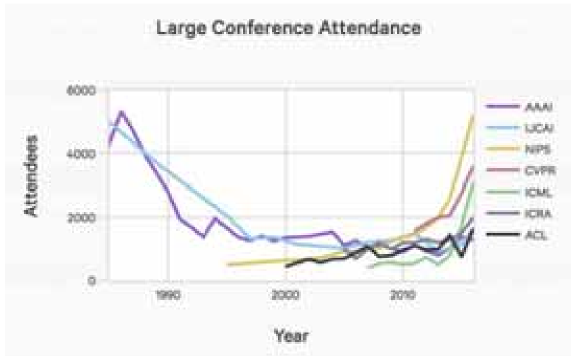
The AI winter was bitter cold …

https://blogs.dxc.technology/2017/04/25/are-we-heading-toward-an-ai-winter/

From AI Hype to AI Winter and the AI Renaissance



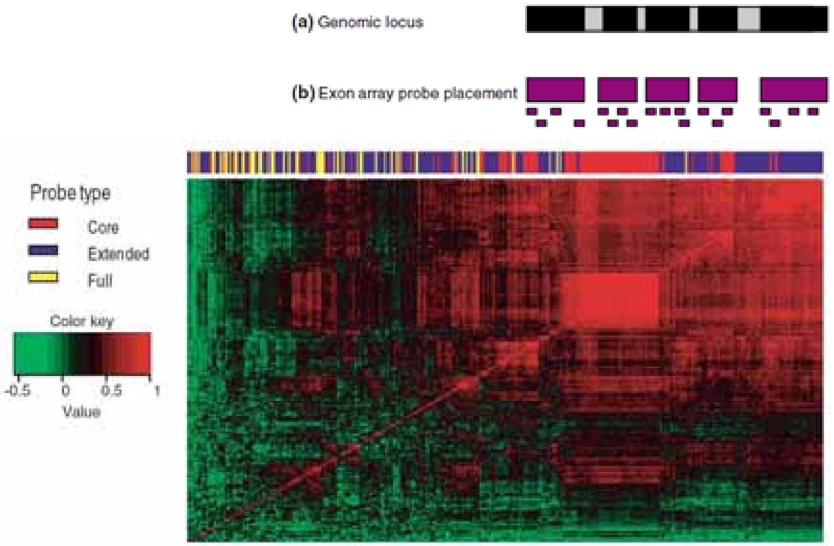
https://www.computer.org/csl/mags/ex/2003/03/x3018.html



https://medium.com/machine-learning-in-practice/nips-accepted-papers-stats-26f124843aa0

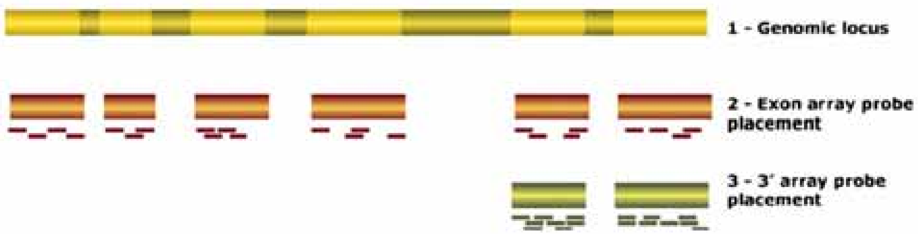
04 Example: P4-Medicine

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.*

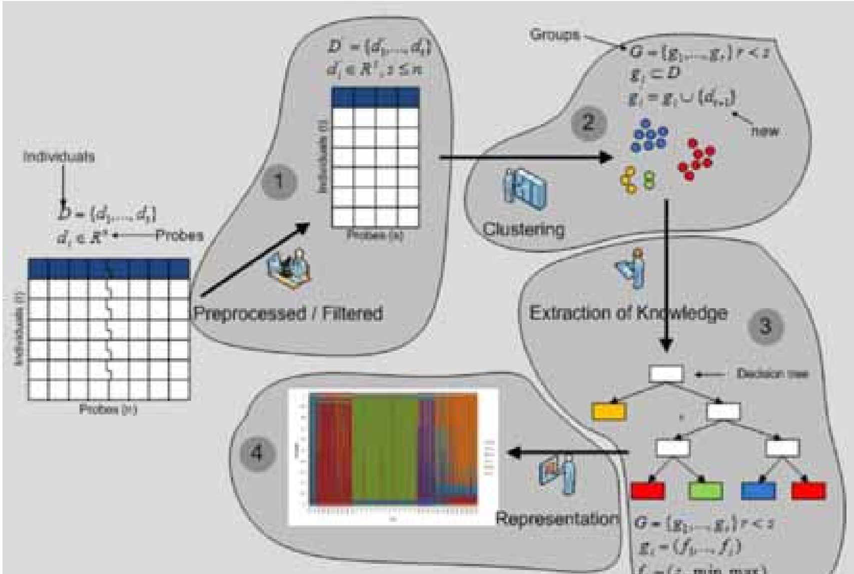
Slide 8-23 Computational leukemia cancer detection 1/6



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



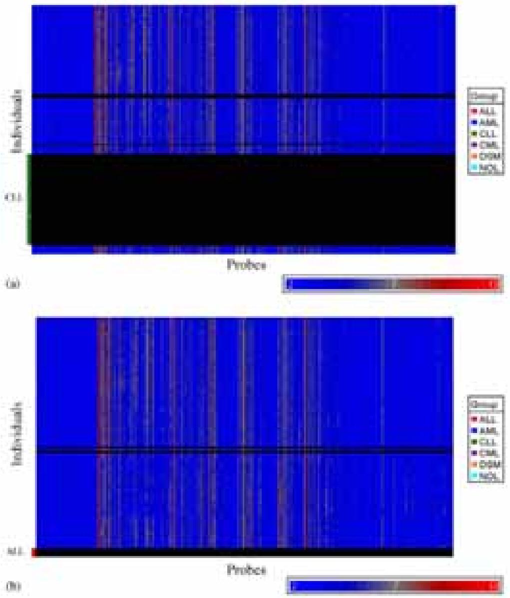
Corchado et al. (2009)

Slide 8-25 Computational leukemia cancer detection 3/6

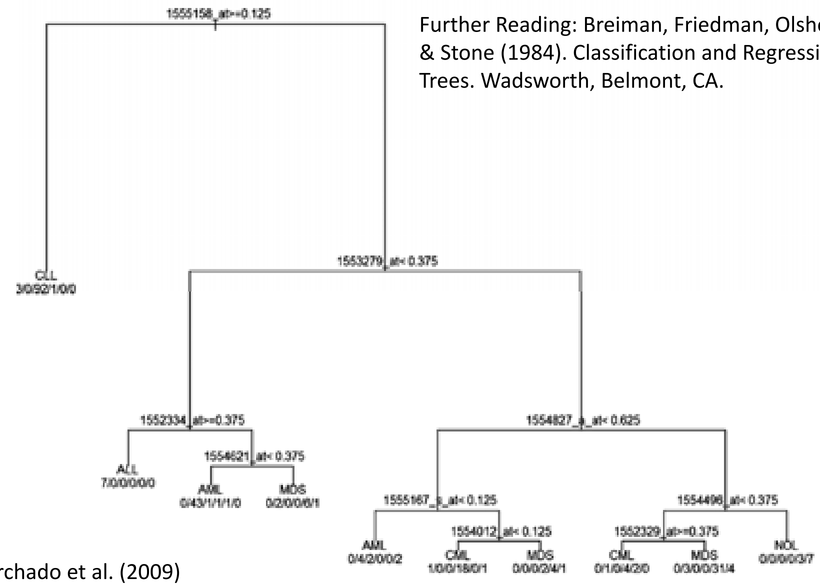
A = acute, C = chronic,
L = lymphocytic, M = myeloid

- **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

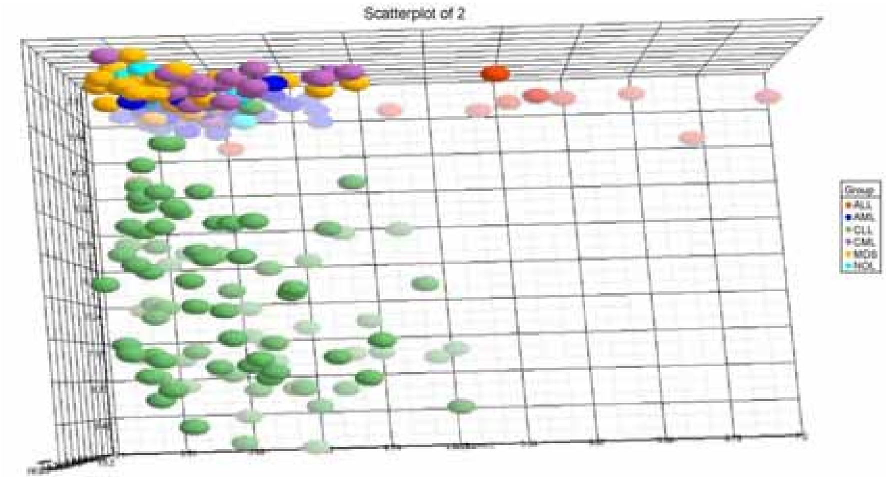


Further Reading: Breiman, Friedman, Olshen, & Stone (1984). Classification and Regression Trees. Wadsworth, Belmont, CA.

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)

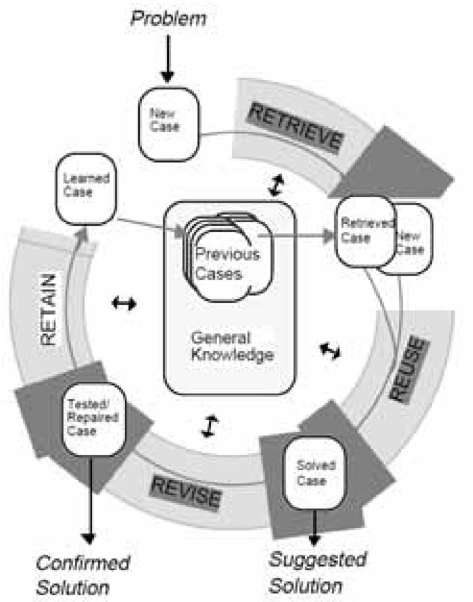
Computational leukemia cancer detection 6/6

- 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

05 Example: Case Based Reasoning (CBR)

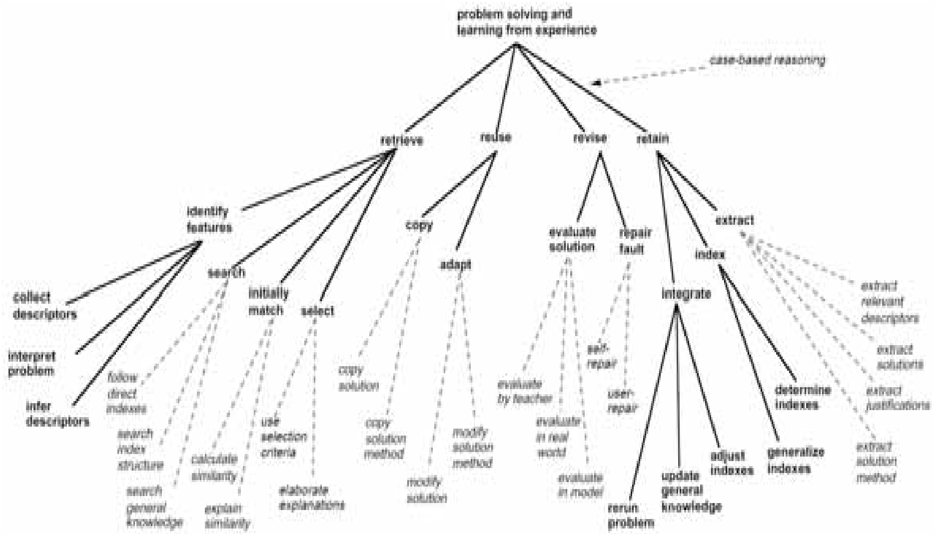
Thinking – Reasoning – Deciding – Acting

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.*

The task-method decomposition of CBR

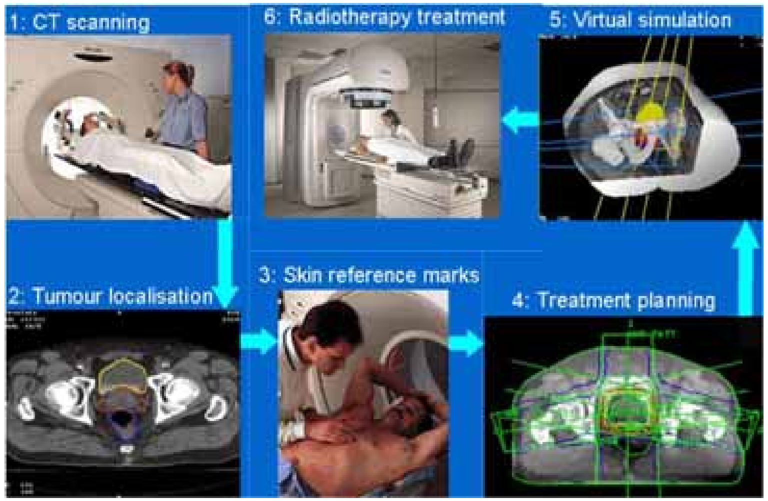


Aamodt & Plaza (1994)

CBR Example: Radiotherapy Planning 1/6

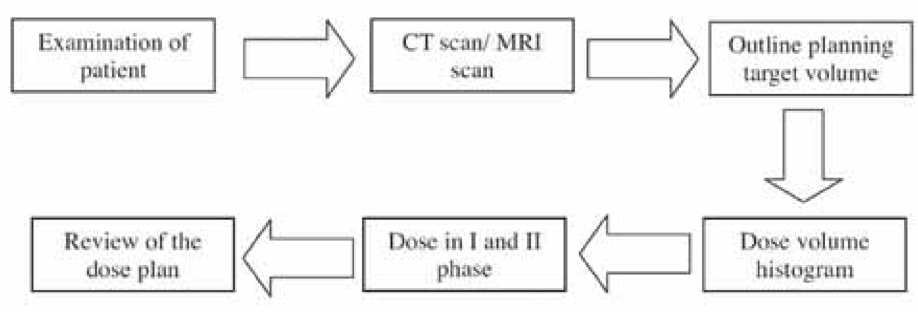
Source: http://www.teachingmedicalphysics.org.uk

CBR Example: Radiotherapy Planning 2/6



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

CBR Example: Radiotherapy Planning 3/6

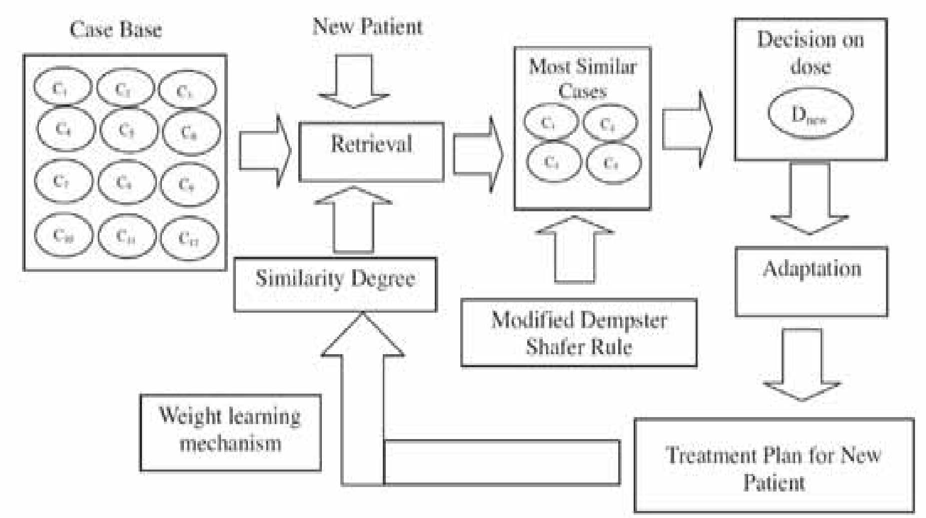


Measures:

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.*

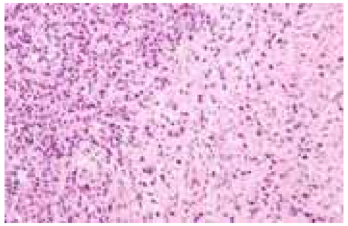
Slide 8-35 CBR System Architecture 4/6

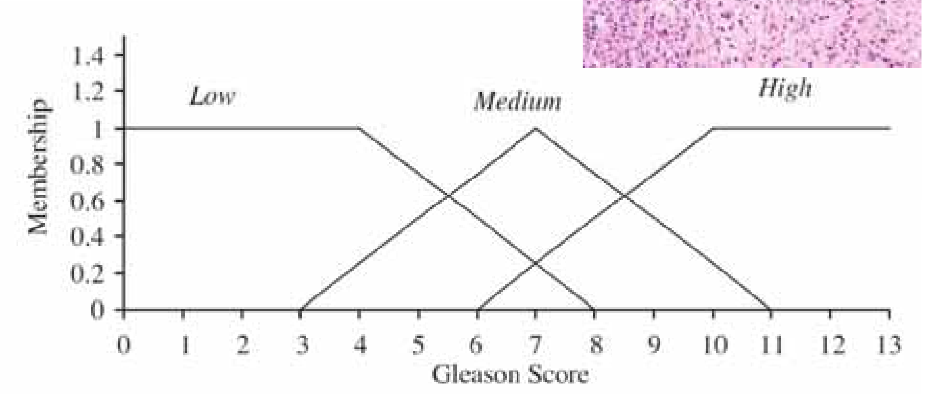


Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

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

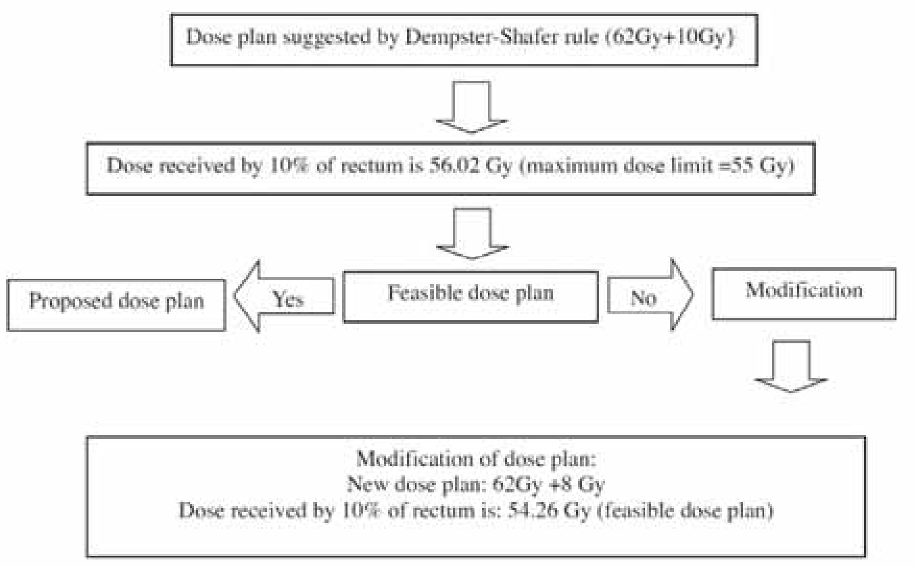




Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications, 38, 9, 10759-10769.*

Slide 8-37 Case Based Reasoning 6/6

Petrovic et al. (2011)



04 Human Information Processing

06 Human Information Processing

Important: Statistics meet Knowledge

- 1. How does abstract knowledge guide learning and inference from sparse data?
  - (Approximate) Bayesian inference in probabilistic models.
- 2. What are the forms and contents of that knowledge?
  - Probabilities defined over a range of structured representations: graphs, grammars, predicate logic, schemas… programs.
- 3. How is that knowledge itself acquired?
  - Hierarchical Bayesian models, with inference at multiple levels of abstraction (“learning to learn”). Learning as (hierarchical Bayesian) program induction.
- **Central Question:**
  How does our mind get so much out of so little?

Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285, doi:10.1126/science.1192788.

Humans can understand the context

15b

- **“How do humans generalize from so few examples?”**
  - Learning relevant representations
  - Disentangling the explanatory factors
  - Finding the shared underlying explanatory factors, in particular between $P(x)$ and $P(Y|X)$, with a causal link between $Y \rightarrow X$

Bengio, Y., Courville, A. & Vincent, P. 2013. Representation learning: A review and new perspectives. IEEE transactions on pattern analysis and machine intelligence, 35, (8), 1798-1828, doi:10.1109/TPAMI.2013.50.

Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285, doi:10.1126/science.1192788.

How does our mind get so much out of so little …

Salakhutdinov, R., Tenenbaum, J. & Torralba, A. 2012. One-shot learning with a hierarchical nonparametric Bayesian model. Journal of Machine Learning Research, 27, 195-207.

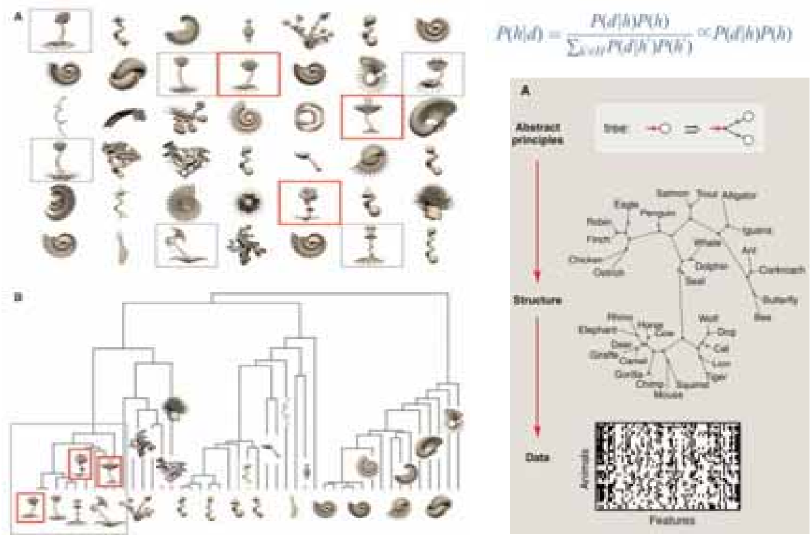
Learning words for objects – concepts from examples

Quaxl Quaxl

Quaxl

Salakhutdinov, R., Tenenbaum, J. & Torralba, A. 2012. One-shot learning with a hierarchical nonparametric Bayesian model. Journal of Machine Learning Research, 27, 195-207.

How do we understand our world …



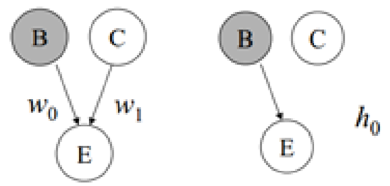
Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285.

One of the unsolved problems in human concept learning

- which is highly relevant for ML research, concerns the factors that determine the subjective difficulty of concepts:
- Why are some concepts psychologically extremely simple and easy to learn,
- while others seem to be extremely difficult, complex, or even incoherent?
- These questions have been studied since the 1960s but are still unanswered …

Feldman, J. 2000. Minimization of Boolean complexity in human concept learning. Nature, 407, (6804), 630-633, doi:10.1038/35036586.

A few certainties

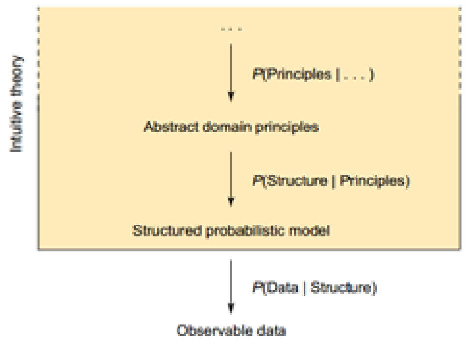


- Cognition as probabilistic inference
  - Visual perception, language acquisition, motor learning, associative learning, memory, attention, categorization, reasoning, causal inference, decision making, theory of mind
- Learning concepts from examples
- Learning and applying intuitive theories (balancing complexity vs. fit)

Modeling basic cognitive capacities as intuitive Bayes

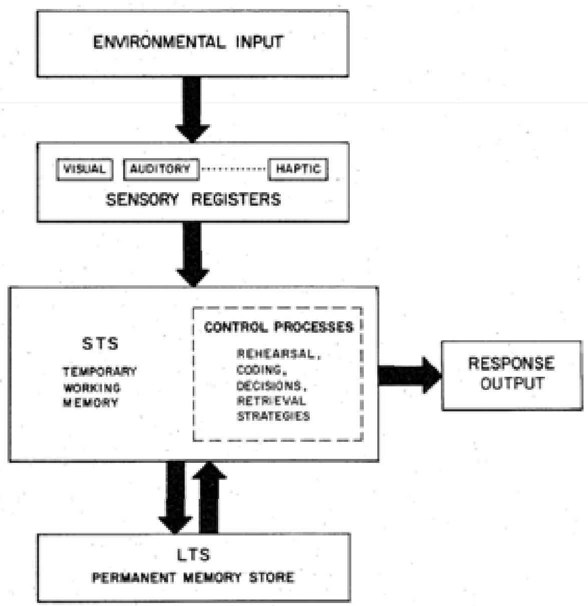
- Similarity
- Representativeness and evidential support
- Causal judgement
- Coincidences and causal discovery
- Diagnostic inference
- Predicting the future

Tenenbaum, J. B., Griffiths, T. L. & Kemp, C. 2006. Theory-based Bayesian models of inductive learning and reasoning. Trends in cognitive sciences, 10, (7), 309-318.

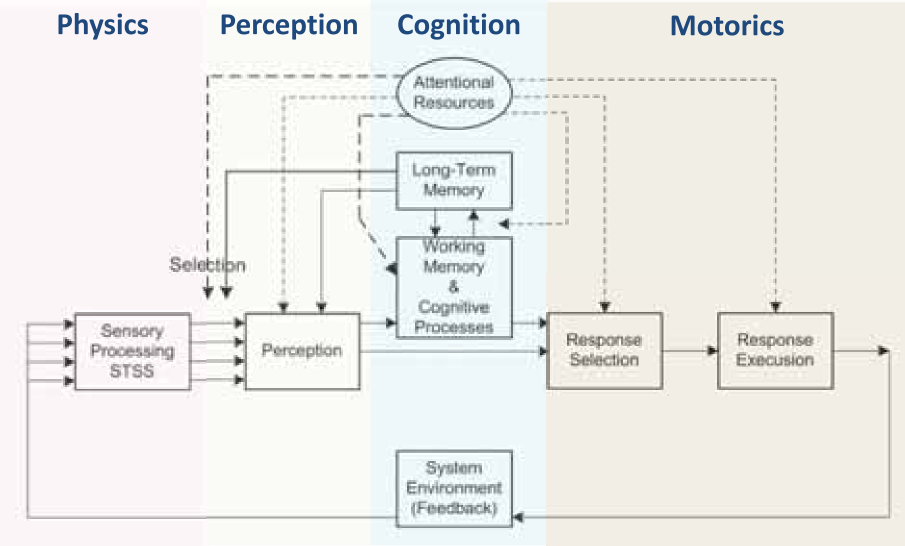


Human Information Processing Model (A&S)

Atkinson, R. C. & Shiffrin, R. M. (1971) *The control processes of short-term memory (Technical Report 173, April 19, 1971). Stanford, Institute for Mathematical Studies in the Social Sciences, Stanford University.*



General Model of Human Information Processing



Wickens, C., Lee, J., Liu, Y. & Gordon-Becker, S. (2004) *Introduction to Human Factors Engineering: Second Edition. Upper Saddle River (NJ), Prentice-Hall.*

Learning and Inference

d … *data*

h … *hypotheses*

$\mathcal{H}$ … $\{H_1, H_2, \dots, H_n\}$ $\forall\, h, d$ …

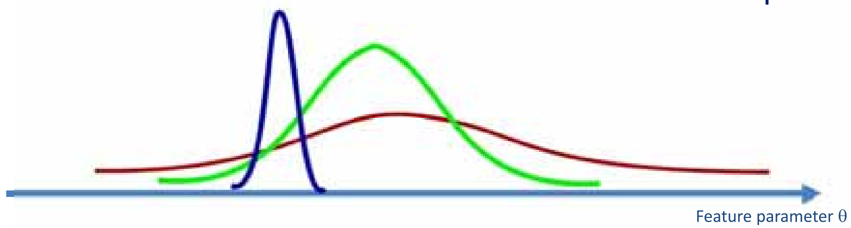
Likelihood

Prior Probability

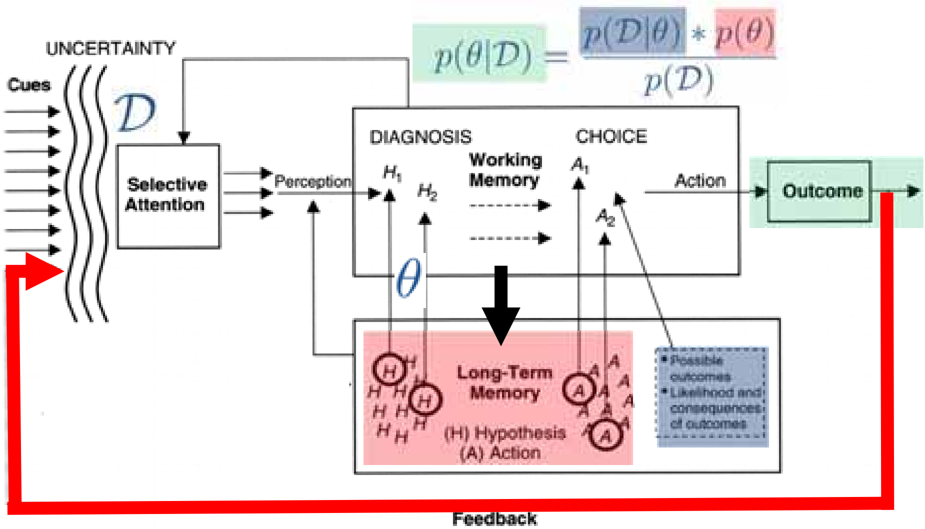
$$p(h|d) = \frac{p(d|h) * p(h)}{\sum_{h \in H} p(d|h')\, p(h')}$$

Posterior Probability

Problem in $\mathbb{R}^n \rightarrow$ complex



Connection to Cognitive Science: Decision Making



Wickens, C. D. (1984) *Engineering psychology and human performance. Columbus (OH), Charles Merrill, modified by Holzinger, A.*

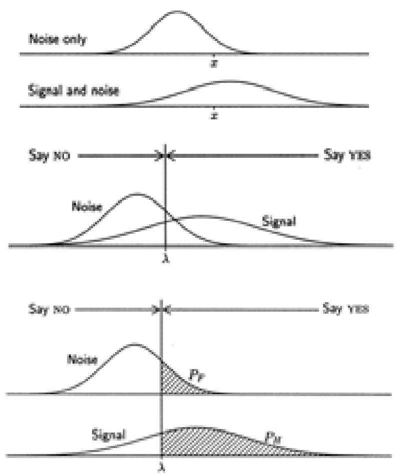
06 How to make decisions in an domain of uncertainty

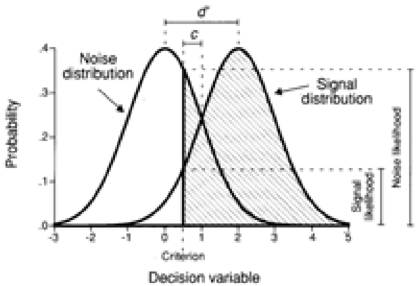
07 Probabilistic Decision Making

"It is remarkable that a science which began with the consideration of games of chance should have become the most important object of human knowledge"
Pierre Simon de Laplace, 1812

Signal Detection Theory (SDT)

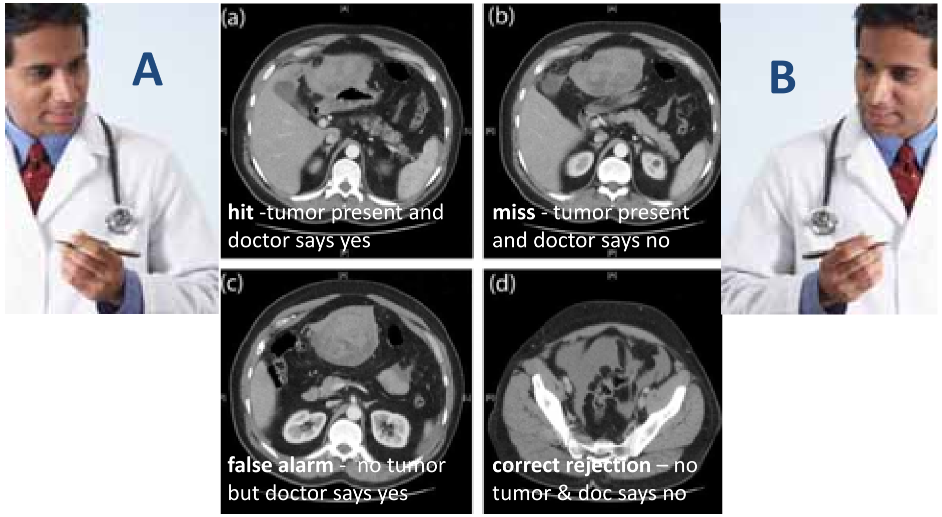
Image source: Staffordshire University Computing Futures Museum http://www.fcet.staffs.ac.uk/jdw1/sucfm/malvern.htm





Stanislaw, H. & Todorov, N. 1999. Calculation of signal detection theory measures. Behavior research methods, instruments, & computers, 31, (1), 137-149.

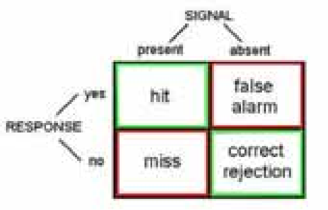
Signal Detection Theory on the MDM process

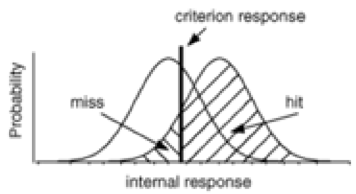


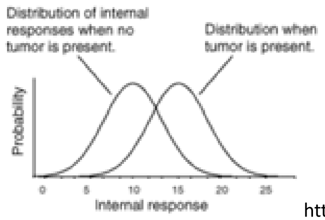
Two doctors, with equally good training, looking at the same CT scan, will have the same information … but they may have a **different bias/criteria!**

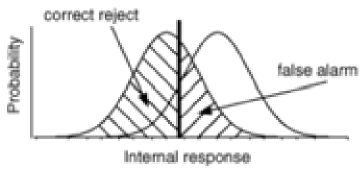
Decision Making Process - Signal Detection

Remember: Two doctors, with equally good training, looking at the same CT scan data, will have the same information … but they may gain different knowledge due to *bias/criteria*.





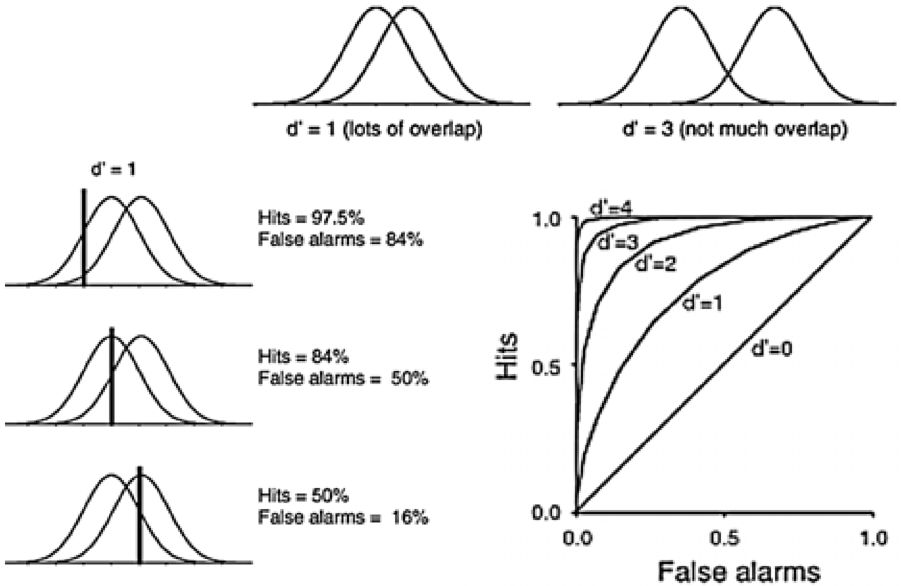




http://www-psych.stanford.edu/~lera/psych115s/notes/signal

For an example see: Braga & Oliveira (2003) Diagnostic analysis based on ROC curves: theory and applications in medicine. *Int. Journal of Health Care Quality Assurance, 16, 4, 191-198.*

Receiver Operating Characteristics (ROC curve)



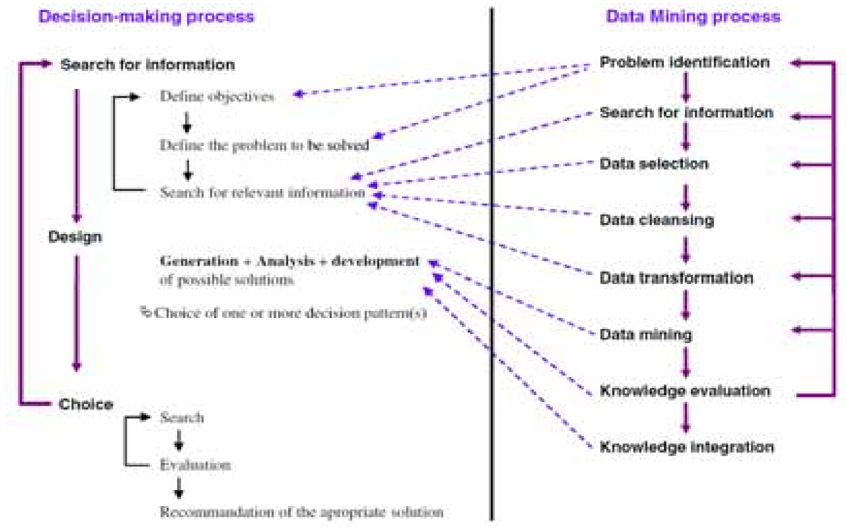
http://gru.stanford.edu/doku.php/tutorials/sdt

Information Acquisition and criteria - bias

- **Information acquisition:** in the CT data, e.g. healthy lungs have a characteristic shape; the presence of a tumor might distort that shape (= anomaly).
- Tumors have different image characteristics: brighter or darker, different texture, etc.
- With proper training a doctor learns what kinds of things to look for, so with more practice/training they will be able to acquire more (and more reliable) information.
- Running another test (e.g., MRI) can be used to acquire more (relevant!) information.
- The effect of information is to increase the likelihood of getting either a hit or a correct rejection, while reducing the likelihood of an outcome in the two error boxes (slide 33).
- **Criterion:** Additionally to relying on technology/testing, the medical profession allows doctors to use their own judgment.
- Different doctors may feel that the different types of errors are not equal.
- For example, a doctor may feel that missing an opportunity for early diagnosis may mean the difference between life and death.
- A false alarm, on the other hand, may result only in a routine biopsy operation. They may chose to err toward ``yes'' (tumor present) decisions.
- Other doctors, however, may feel that unnecessary surgeries (even routine ones) are very bad (expensive, stress, etc.).
- They may chose to be more conservative and say ``no'' (no turmor) more often. They will miss more tumors, but they will be doing their part to reduce unnecessary surgeries. And they may feel that a tumor, if there really is one, will be picked up at the next check-up.

Mohamed, A. et al. (2010) Traumatic rupture of a gastrointestinal stromal tumour with intraperitoneal bleeding and haematoma formation. *BMJ Case Reports, 2010.*

Decision Making Process vs. Data Mining process



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

Repetition Bayes Foundations

What is the simplest mathematical operation for us?

$$p(x) = \sum_{x}(p(x,y))$$

How do we call repeated adding?

$$p(x,y) = p(y|x) * p(y)$$

Laplace (1773) showed that we can write:

$$p(x,y) * p(y) = p(y|x) * p(x)$$

Now we introduce a third, more complicated operation:

$$\frac{p(x,y) * p(y)}{p(y)} = \frac{p(y|x) * p(x)}{p(y)}$$

We can reduce this fraction by $p(y)$ and we receive what is called Bayes rule:

$$p(x,y) = \frac{p(y|x) * p(x)}{p(y)} \qquad p(h|d) = \frac{p(d|h)p(h)}{p(d)}$$

Bayes Law of Total Probability = data modelling

d … data; h … hypothesis

$$P(h|d) = \frac{P(d|h)P(h)}{P(d)}$$

$P(h)$: prior belief (probability of hypothesis h before seeing any data)

$P(d\,|\,h)$: likelihood (probability of the data if the hypothesis h is true)

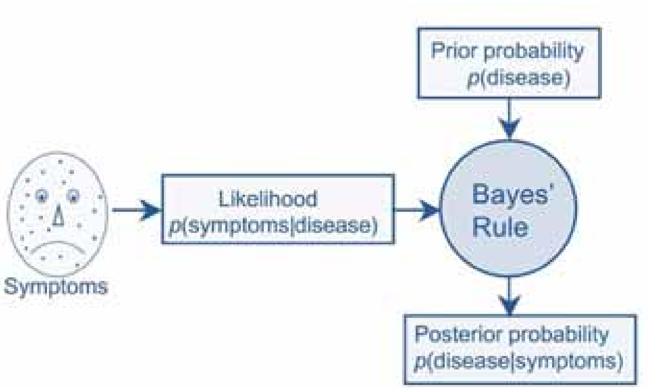
$P(d) = \sum_{h} P(d\,|\,h)P(h)$: data evidence (marginal probability of the data)

$P(h\,|\,d)$: posterior (probability of hypothesis h after having seen the data d)

$$posterior = \frac{likelihood * prior}{evidence}$$

- **evidence = marginal likelihood = "normalization"**
- **Remember: The inverse probability allows to infer unknowns, learn from data and make predictions … machine learning!**

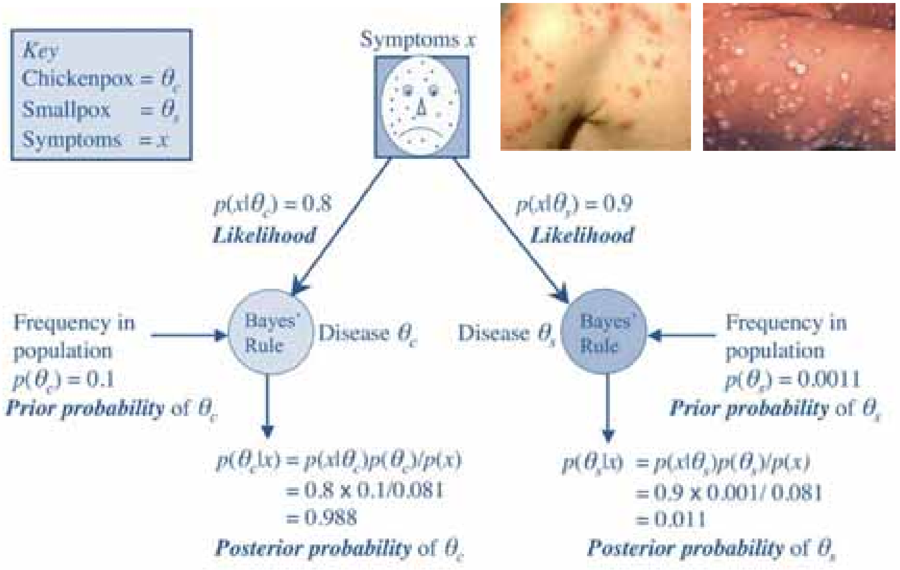
Bayes Rule for Medical Diagnosis



$$p(\text{disease}|\text{symptoms}) = \frac{p(\text{symptoms}|\text{disease})p(\text{disease})}{p(\text{symptoms})}$$

Stone, J. V. 2013. Bayes' rule: a tutorial introduction to Bayesian analysis. Sebtel Press.

Bayesian Inference



Practical Example: Diagnoses

- Your MD has bad news and good news for you.
- Bad news first: You are tested positive for a serious disease, and the test is 99% accurate if you are infected (T)
- Good news: It is a rare disease, striking 1 in 10,000 (D)
- **How worried would you now be?**

$$posterior\ p(x) = \frac{likelihood * prior\ p(x)}{evidence} \qquad p(h|d) = \frac{p(d|h)p(h)}{p(d)}$$

$$p(T=1|D=1) = p(d|h) = 0{,}99 \ \ and$$
$$p(D=1) = p(h) = 0{,}0001$$

$$p(D=1\,|\,T=1) = \frac{(0{,}99)*(0{,}0001)}{(1-0{,}99)*(1-0{,}0001)+0{,}99*0{,}0001} =$$

= 0,0098

Problem Solving: Humans vs. Computers

When is the human *) better?

*) human intelligence/natural intelligence/human mind/human brain/ learning

- **Natural Language Translation/Curation**
  Computers cannot understand the context of sentences [3]
- **Unstructured problem solving**
  Without a pre-set of rules, a machine has trouble solving the problem, because it lacks the creativity required for it [1]
- **NP-hard Problems**
  Processing times are often exponential and makes it almost impossible to use machines for it, but human make heuristic decisions which are often not perfect but sufficiently good [4]

When is the computer **) better?

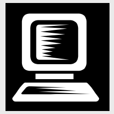
**) Computational intelligence, Artificial Intelligence/soft computing/ML

- **High-dimensional data processing**
  Humans are very good at dimensions less or equal than 3, but computers can process data in arbitrarily high dimensions
- **Rule-Based environments**
  Difficulties for humans in rule-based environments often come from not recognizing the correct goal in order to select the correct procedure or set of rules [2]
- **Image optimization**
  Machine can look at each pixel and apply changes without human personal biases, and with more speed [1]

[1] Kipp, M. 2006. Creativity Meets Automation: Combining Nonverbal Action Authoring with Rules and Machine Learning. In: LNCS 4133, pp. 230-242, doi:10.1007/11821830_19.
[2] Cummings, M. M. 2014. Man versus Machine or Man + Machine? IEEE Intelligent Systems, 29, (5), 62-69, doi:10.1109/MIS.2014.87.
[3 Pizlo, Z., Joshi, A. & Graham, S. M. 1994. Problem Solving in Human Beings and Computers. Purdue TR 94-075.
[4] Griffiths, T. L. Connecting human and machine learning via probabilistic models of cognition. Interspeech, 2009, ISCA, 9-12..

Comparison

Human vs. Computer



Human	Computer
sensitiveness for stimuli (visual, auditory, tactile, olfactory)	Precise Counting and Measuring of physical entities
Ability for inductive Reasoning and complex Problem Solving	Deductive Operations, formal Logic, Application of Rules
Creating of networked knowledge and storage for a live-long time	Storage of huge amounts of data which are not necessarily connected
Flexibility in decisions, even in totally new situations	Reliable reaction to unambiguous input signals
Discovering of ambiguous signals even when distorted	Reliable performance over long periods without tiredness

Holzinger, A. 2000. *Basiswissen Multimedia 2: Lernen. Kognitive Grundlagen multimedialer Informationssysteme,* Würzburg, Vogel.

Conclusion

- Computers are incredibly fast, accurate and stupid,
- humans are incredibly slow, inaccurate and brilliant,
- together they are powerful beyond imagination

(Einstein never said that)

https://www.benshoemate.com/2008/11/30/einstein-never-said-that

Thank you!

Questions

Reflection from last lecture

- The Quiz-Slide will be shown during the course