

Mini Course

Fundamentals of Medical Al

Part 03

From Decision Making to Decision Support

Andreas Holzinger

Human-Centered AI Lab (Holzinger Group)
Institute for Medical Informatics/Statistics, Medical University Graz, Austria and

Explainable AI-Lab, Alberta Machine Intelligence Institute, Edmonton, Canada





Primer on Probability & Information

Part 1 Theory

01 Introduction to Medical AI and Machine Learning for Health

02 Data, Information and Knowledge

03 Human Decision Making and Al Decision Support

04 Causal Reasoning and Interpretable AI

Part 2 Practice

05 Methods of Explainable AI

06 Social, Ethical and Legal Aspects of Medical Al

07 Project: Bringing AI into medical workflows

08 Presentation of the developed concepts



- 00 Reflection follow up from last lecture
- 01 Medical Action = Decision Making
- 02 Can AI help doctors to make better decisions?
- 03 Human Information Processing
- 04 Probabilistic Decision Theory
- 05 Example: P4 Medicine
- 06 Example: Case Based Reasoning
- Conclusion



00 Reflection

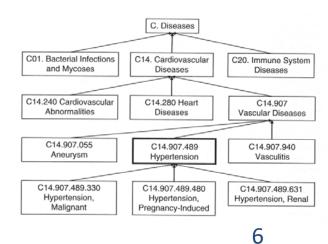
Reflection from last lecture













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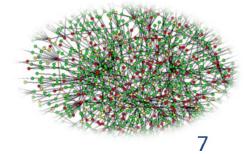
Α

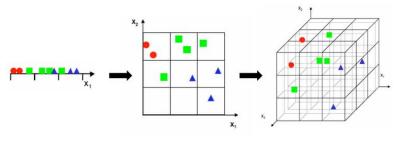
24184005|Finding of increased blood pressure (finding) → 38936003|Abnormal blood pressure (finding) AND roleGroup SOME (363714003|Interprets (attribute) SOME 75367002|Blood pressure (observable entity))

В

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

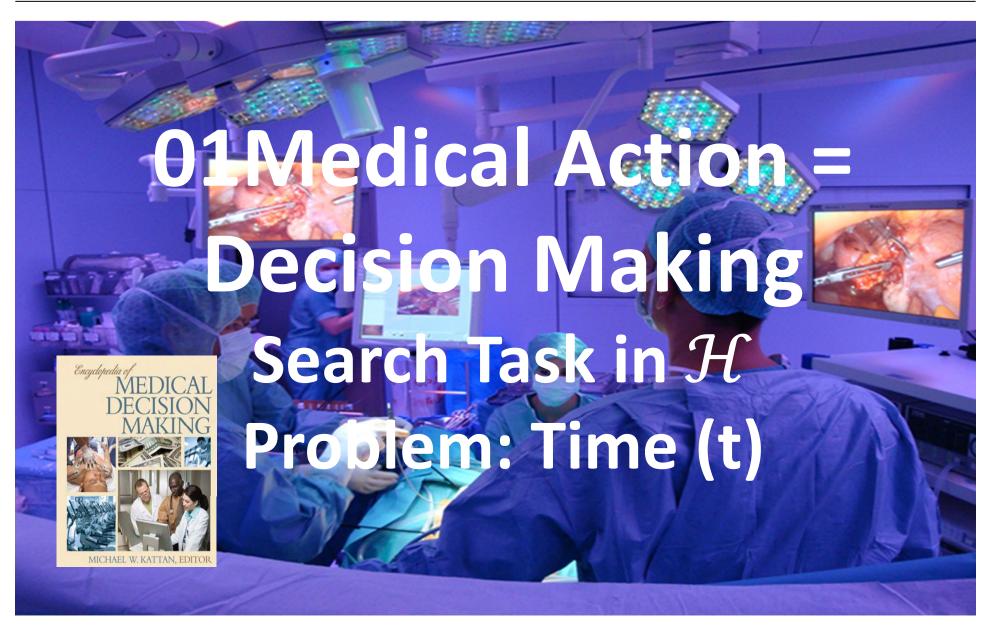
363714003|Interprets (attribute) SOME 75367002|Blood pressure (observable entity))





8





Michael W. Kattan (ed.) (2009). Encyclopedia of medical decision making, London: Sage.

What is the main limitation in decision making?





Decision Making is central in any (medical) work!





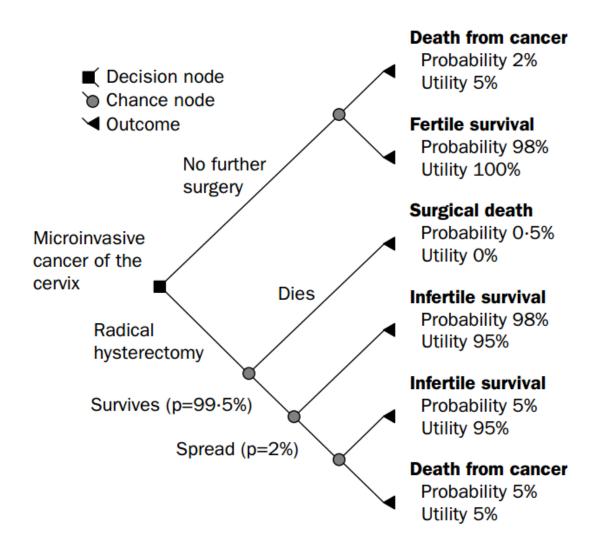
What are the roots of medical decision making?



- 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 – 1890 (!)
 - this is exactly what current AI/machine learning is tackling - prediction models are based on data features, patient health status is modelled as high-dimensional feature vectors ...

Where are decision trees coming from?







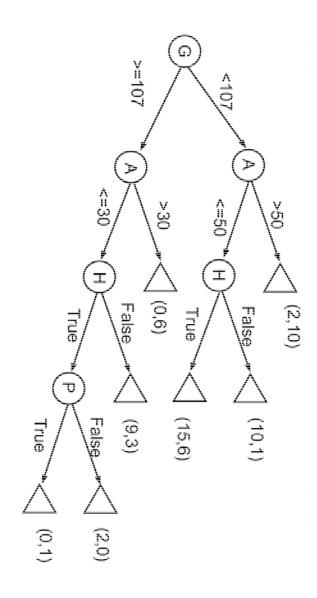
Physician treating a patient approx. 480 B.C.
Beazley (1963), Attic Red-figured Vase-Painters, 813, 96.
Department of Greek, Etruscan and Roman Antiquities, Sully, 1st floor, Campana Gallery, room 43 Louvre, Paris

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

Decision forests > decision tree > "interpretable AI"



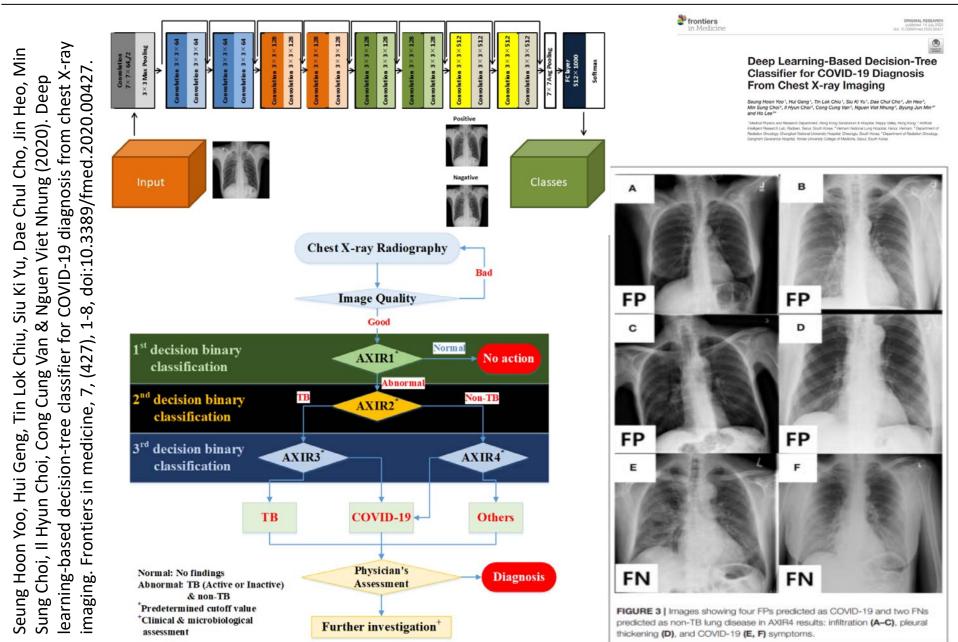
Omer Sagi & Lior Rokach (2020). Explainable decision forest: Transforming decision forest into an interpretable tree. Information Fusion, 61, 124-138, doi:10.1016/j.inffus.2020.03.013



```
Algorithm 1: Generate a decision tree using an existing decision forest
   Input: T (A set of n decision trees \{t_0, t_1, ...t_n\}), D_{pruning} (pruning
            dataset), forest_min_size (minimum forest size), L (Maximum
            size of conjunctions at each iteration)
   Output: DT (a decision tree)
 1 T' = \{\} - Pruned decision forest, AUC_{T'}(D_{pruning}) = 0
2 while AUC_{T'}(D_{pruning}) was improved or |T'| < forest\_min\_size do
       Add to T' the decision tree t from T that maximizes
        AUC_{T'}(D_{pruning})
 5 for each decision tree t_i in T' do
       if i = 0 then
           CS_0 =conjunction set of t_0
            (CS_i = \{(c_{i1}, \hat{y}_{c_{i1}}), (c_{i2}, \hat{y}_{c_{i2}})...(c_{iJ}, \hat{y}_{c_{iJ}})\} where c_{ij} is a
            conjunction of rules and \hat{y}_{c_i} is a vector of classes probabilities
       \mathbf{end}
       else
           CS_i = \{\};
10
           for leaf c_i in t_i do
11
               for conjunction c_k in CS_{i-1} do
12
                   if c_i does not contradict c_k then
13
                      add (c_j \wedge c_k, \hat{y}_{c_i} + \hat{y}_{c_k}) to CS_i
14
                   end
15
               end
16
17
           end
           order CS_i by P(c_{ij})
18
           CS_i = \text{top } L \text{ conjunctions in } CS_i
19
20
21 end
22 Define DT as a single node that contains CS_{|T'|}
23 for each node at DT that wasn't splitted or defined as a leaf do
       for each splitting candidate rule r_{ij} in \{r_{11}, r_{12}...r_{iL}\} do
           Find Information Gain IG from split(CS_{node}, r_{ij})
25
26
       define r' as the attribute with the highest information gain
27
       if IG(r') = 0 then
28
           define current node as a leaf
29
       \mathbf{end}
30
       else
31
           split current node by r'
32
       end
33
34 end
```

Decision trees state of the art in 2020 for Covid-19





How to ensure quality measures?

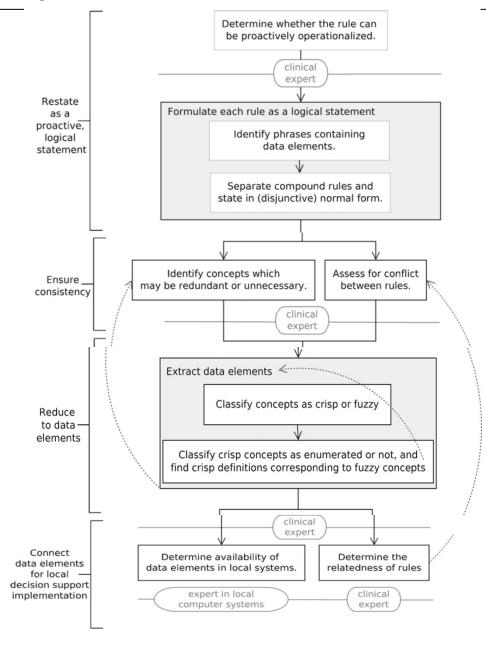


- Clinical guidelines are systematically developed documents to assist doctors and patient decisions about appropriate care;
- In order to build DS, based on a guideline, it is formalized (transformed from natural language to a logical algorithm), and
- implemented (using the algorithm to program a DSS);
- To increase the quality of care, they must be linked to a <u>process of care</u>, <u>f</u>or 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

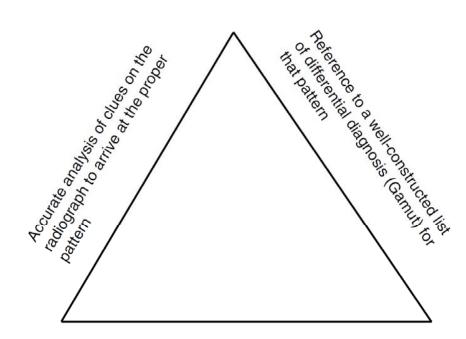


Medlock, S., Opondo, D., Eslami, S., Askari, M., Wierenga, P., de Rooij, S. E. & Abu-Hanna, A. (2011) LERM (Logical Elements Rule Method): A method for assessing and formalizing clinical rules for decision support. International Journal of Medical Informatics, 80, 4, 286-295.



Classical Example: Triangulation to find diagnoses





Correlation of radiographic findings and Gamut with patients' clinical and lab findings to arrive at the most likely diagnosis

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)
- Neoplastic invasion or compression (esp. carcinoma of lung)

UNCOMMON

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

Reference

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

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

UNCOMMON

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

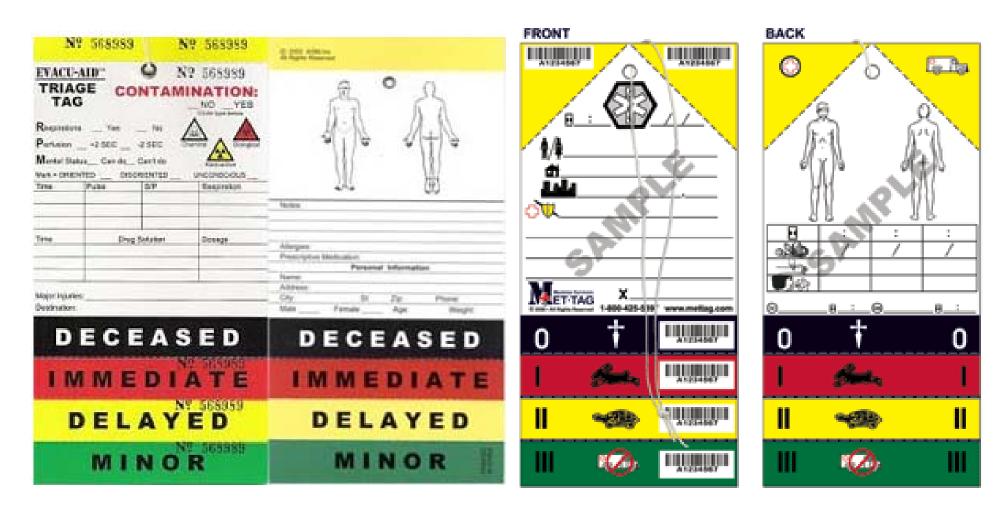
[] This condition does not actually cause the gamuted imaging finding, but can produce imaging changes that simulate it.

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

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

What is the simplest decision support process?

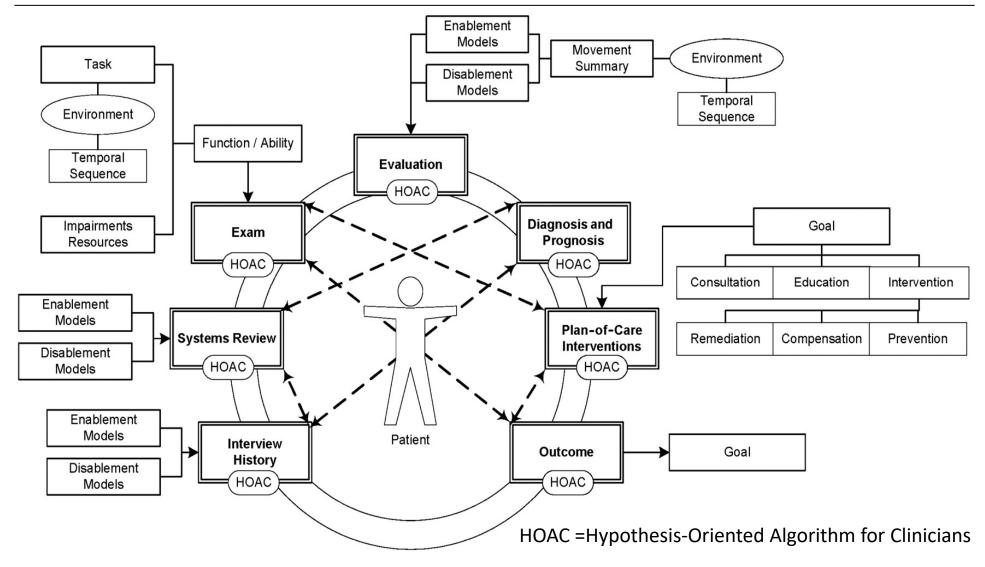




Iserson, K. V. & Moskop, J. C. 2007. Triage in Medicine, Part I: Concept, History, and Types. Annals of Emergency Medicine, 49, (3), 275-281.

Example Clinical DSS: Hypothesis-Oriented Algorithm





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



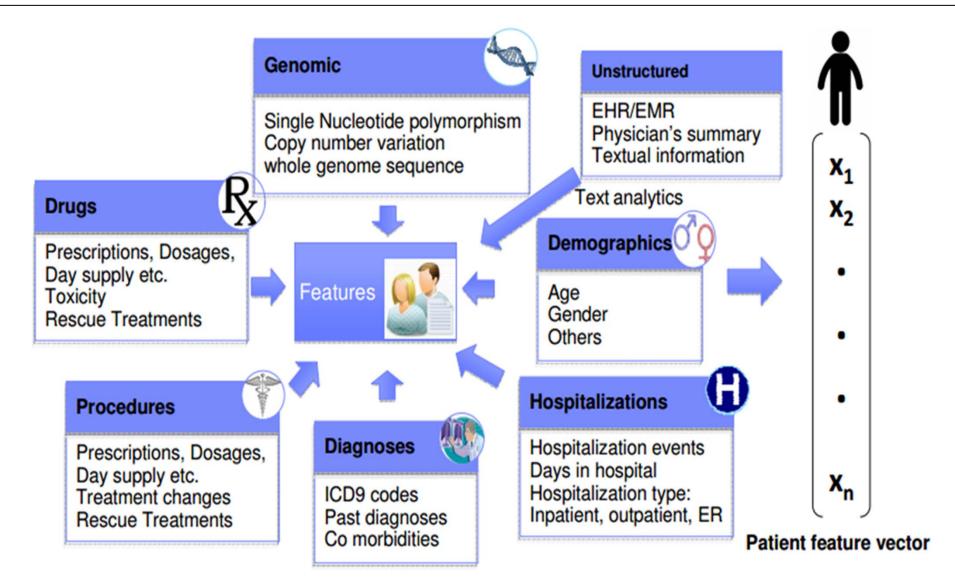


Image credit to Michal Rosen-Zvi



02 Can Al help doctors to make better decisions?

What are the two types of decisions?



- **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





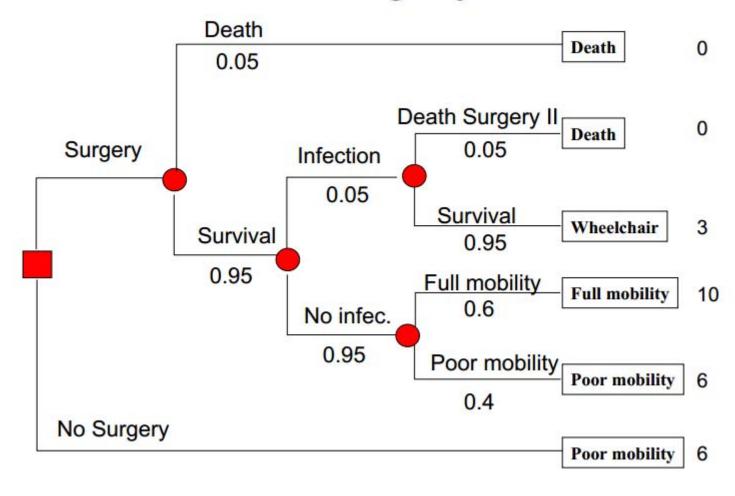
Harvard-MIT Division of Health Sciences and Technology

HST.951J: Medical Decision Support, Fall 2005

Instructors: Professor Lucila Ohno-Machado and Professor Staal Vinterbo

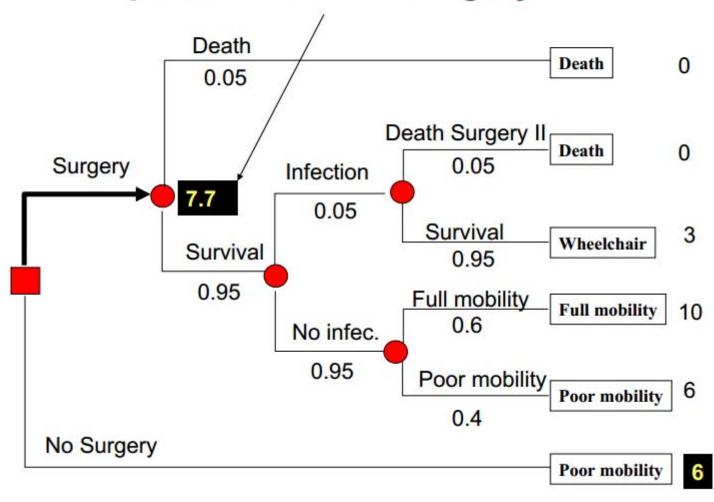


Knee Surgery



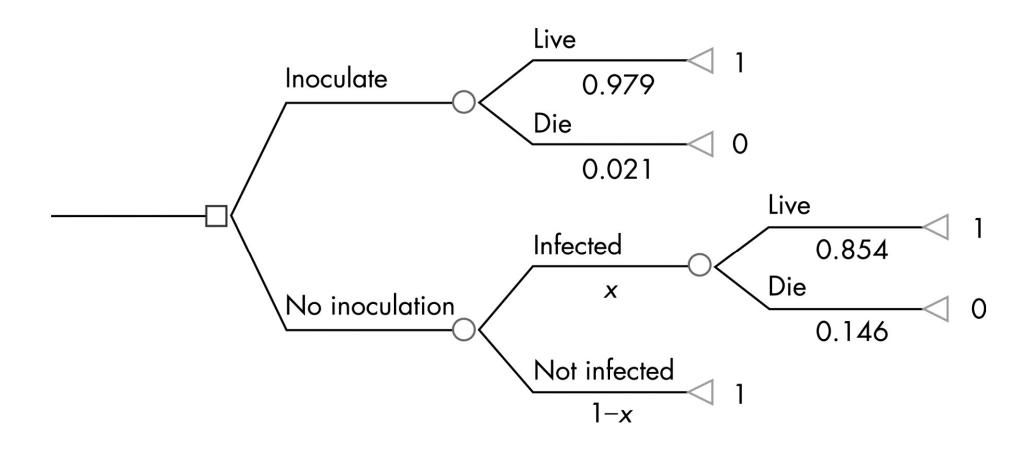


Expected Value of Surgery



Example: Clinical Decision Tree (CDT)





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 $E\left(U|d\right)$



For a single decision variable an agent can select

 $D = d \text{ for any } d \in dom(D).$

The expected utility of decision D = d is ...

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



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

An optimal single decision is the decision $D=d_{max}$ whose expected utility is maximal:

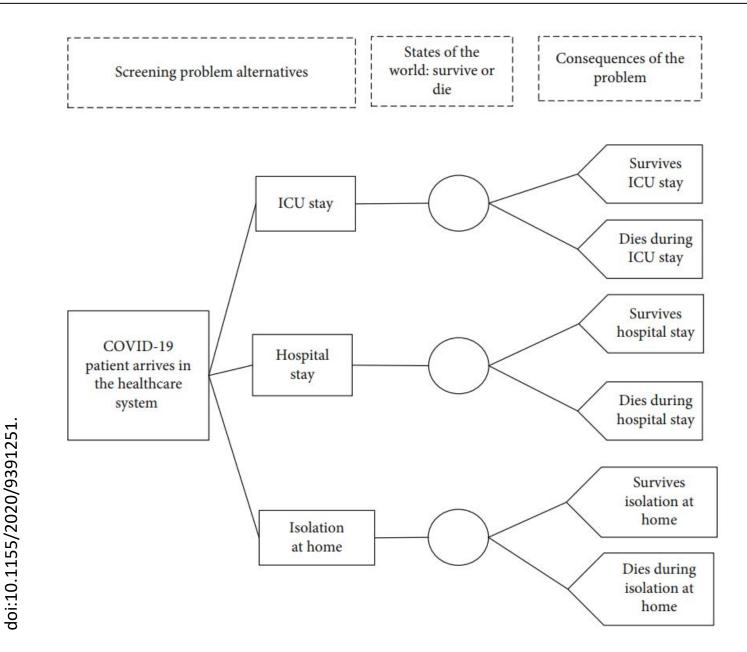
$$d_{\max} = \arg \max_{d \in \text{dom}(D)} E(U \mid d)$$

John Von Neumann & Oskar Morgenstern (1944). *Theory of games and economic behavior*, Princeton, Princeton University Press.

Expectation Maximization Algorithm

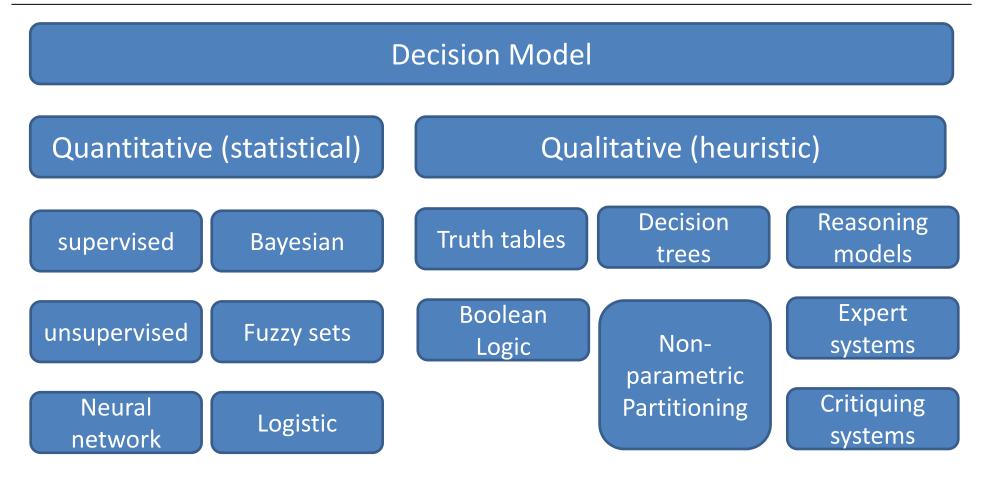


Alexandre Ramalho Alberti & Adiel Teixeira De Almeida (2020). Utility-Based Lucia Reis Peixoto Roselli, Eduarda Asfora Frej, Rodrigo José Pires Ferreira, Pandemic. 9391251, Multicriteria Model for Screening Patients under the COVID-19 Computational and Mathematical Methods in Medicine, 2020,



What are the "classic" Decision Support Models?





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



03 Human Information Processing

What are the pressing open questions?



- 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,
- 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.



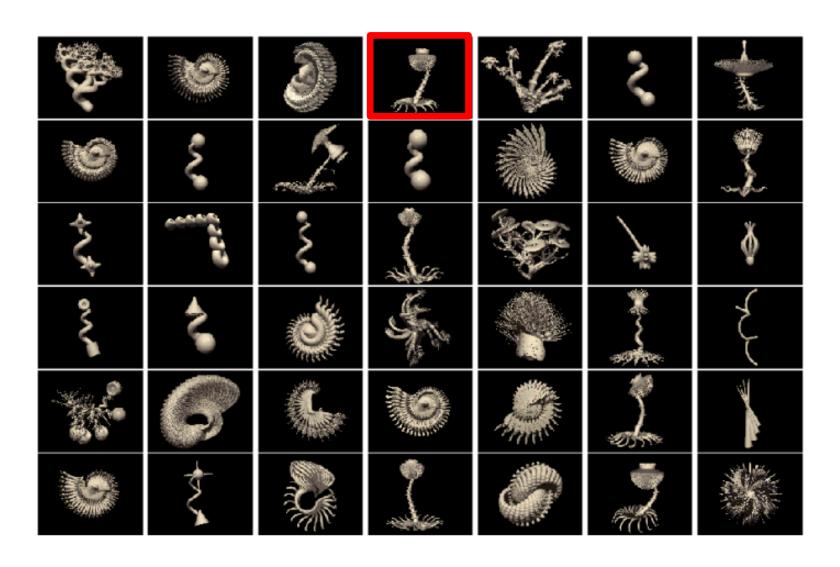
(Sometimes – **not** always!) humans are able ...

- to <u>understand</u> the context
- to make inferences <u>from little</u>, noisy, incomplete data sets
- to learn <u>relevant</u> representations
- to find shared <u>underlying explanatory</u> factors,
- in particular between P(x) and P(Y|X), with a <u>causal link</u> between $Y \rightarrow X$

Joshua B. Tenenbaum, Charles Kemp, Thomas L. Griffiths & Noah D. Goodman 2011. How to grow a mind: Statistics, structure, and abstraction. *Science*, 331, (6022), 1279-1285, doi:10.1126/science.1192788.

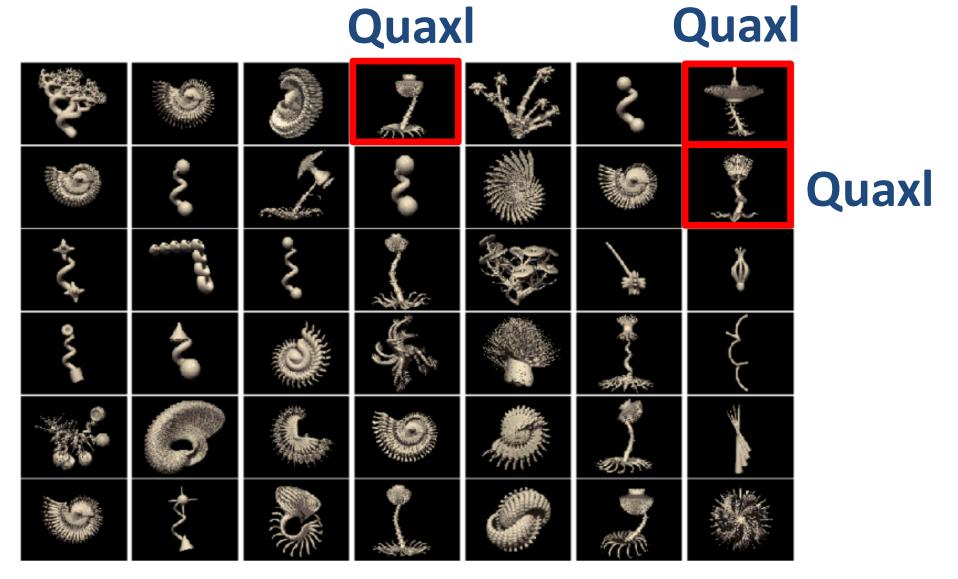
How does our mind get so much out of it?





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

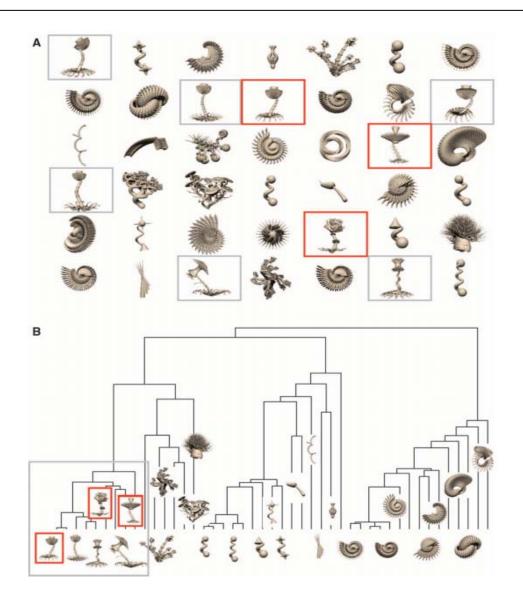




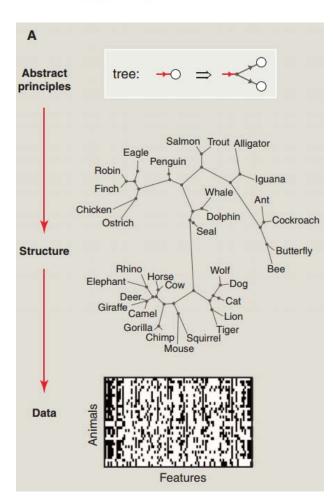
Salakhutdinov, R., Tenenbaum, J. & Torralba, A. 2012. One-shot learning with a hierarchical nonparametric Bayesian model. Journal of Machine Learning Research, 27, 195-207.

How do we understand our world?





$$P(h|d) = \frac{P(d|h)P(h)}{\sum_{h' \in H} P(d|h')P(h')} \propto P(d|h)P(h)$$



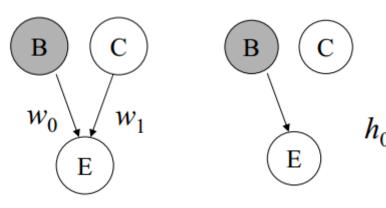
Tenenbaum, J. B., Kemp, C., Griffiths, T. L. & Goodman, N. D. 2011. How to grow a mind: Statistics, structure, and abstraction. Science, 331, (6022), 1279-1285.



- 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.







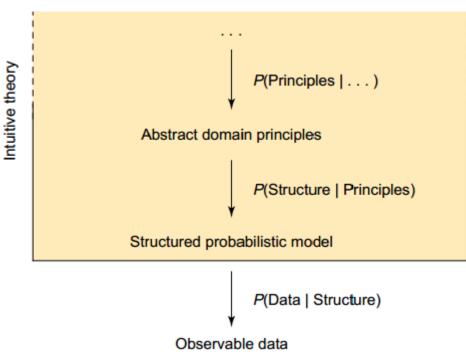


- Cognition as probabilistic inference
 - Visual perception, language acquisition, motor learning, associative learning, memory, attention, categorization, reasoning, causal inference, decision making, theory of mind
- Learning concepts from examples
- Learning and applying intuitive theories (balancing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



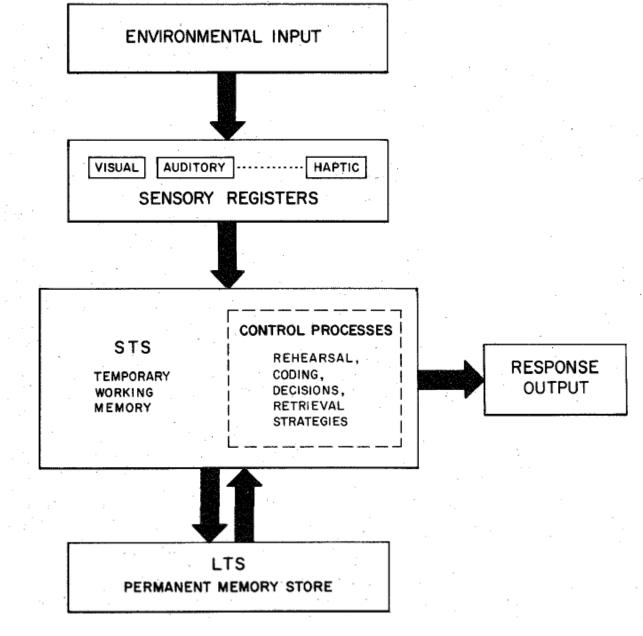
- Similarity
- Representativeness and evidential support
- Causal judgement
- Coincidences and causal discovery
- Diagnostic inference
- Predicting the future

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.



How does the STS/LTS model work?

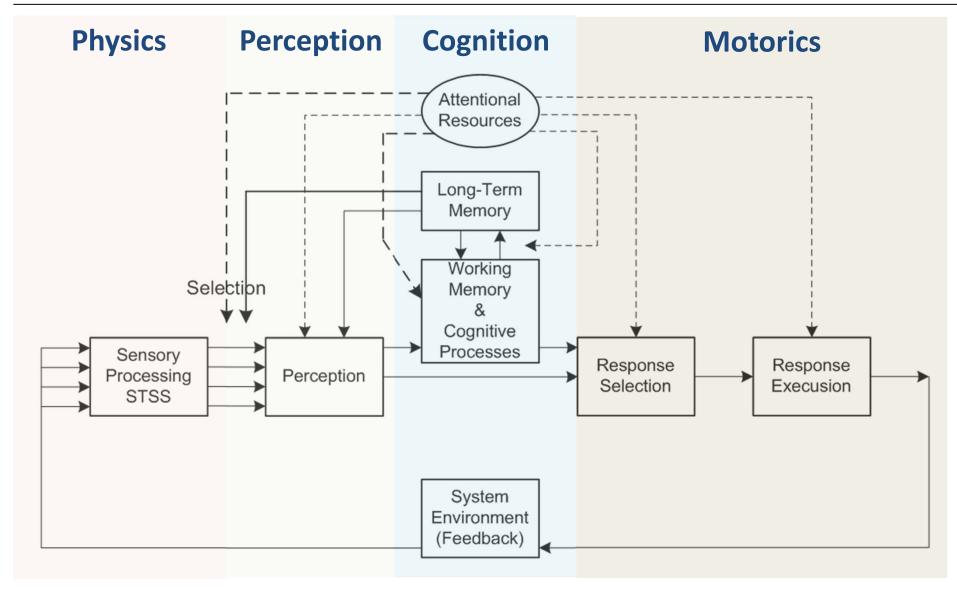




Atkinson, R. C. & Shiffrin, R. M. (1971) The control processes of short-term memory (Technical Report 173, April 19, 1971). Stanford, Institute for Mathematical Studies in the Social Sciences, Stanford University.

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.*

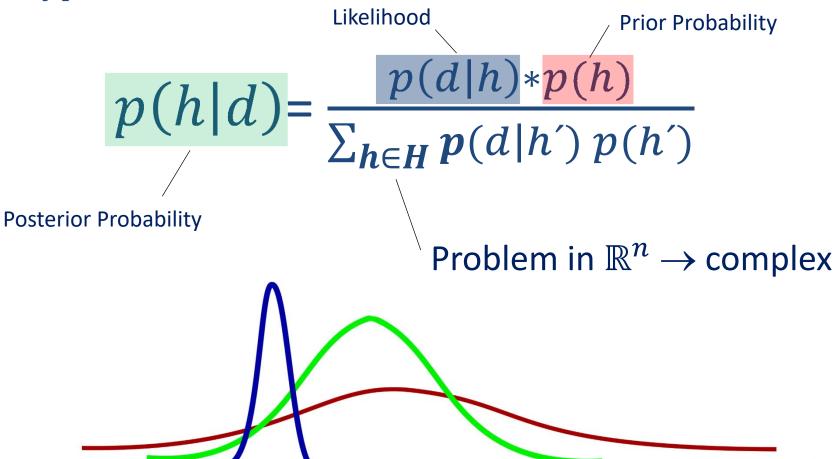


04

d ... data

$$\mathcal{H} \{H_1, H_2, ..., H_n\} \quad \forall h, d$$

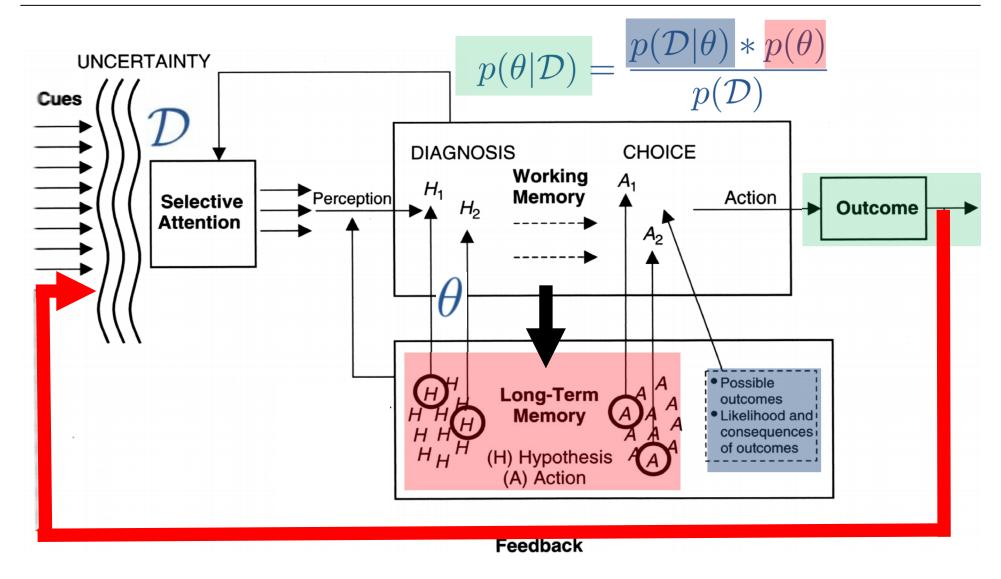
h ... hypotheses



Feature parameter θ

Connection to Cognitive Science: Decision Making





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



04 Probabilistic Decision Making

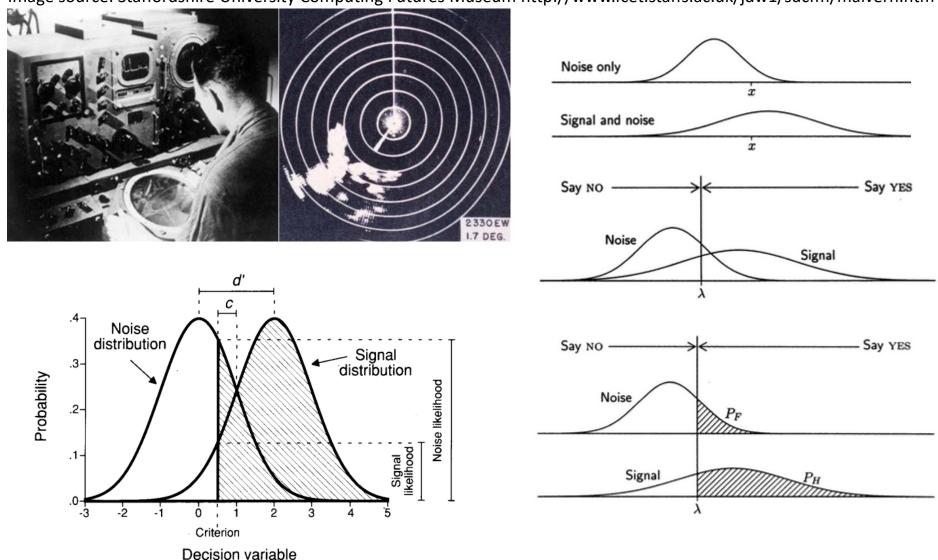
"It is remarkable that a science which began with the consideration of games of chance should have become the most important object of human knowledge"

Pierre Simon de Laplace, 1812

What is Signal Detection Theory (SDT) doing?



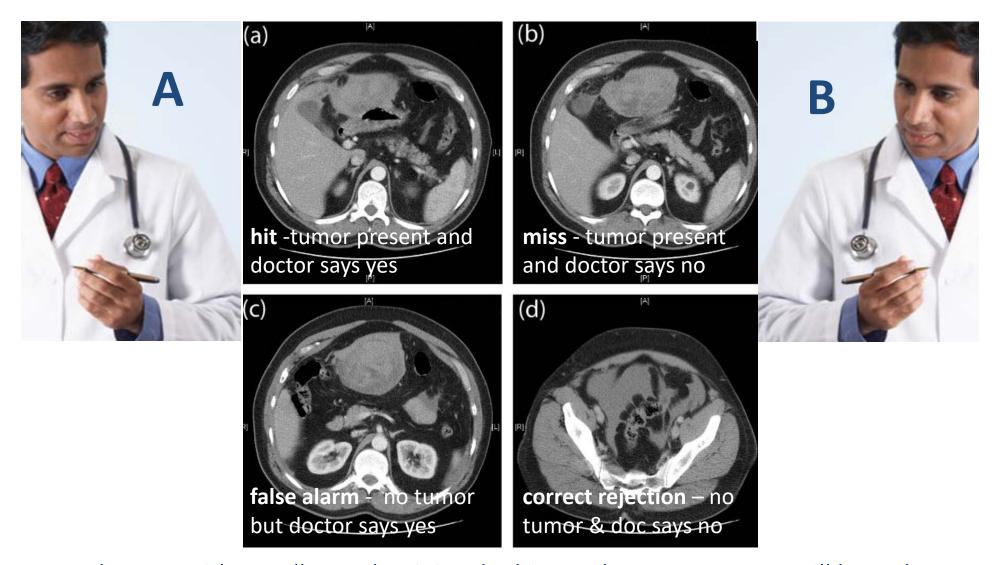
Image source: Staffordshire University Computing Futures Museum http://www.fcet.staffs.ac.uk/jdw1/sucfm/malvern.htm



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

How is Signal Detection Theory applied in medicine?



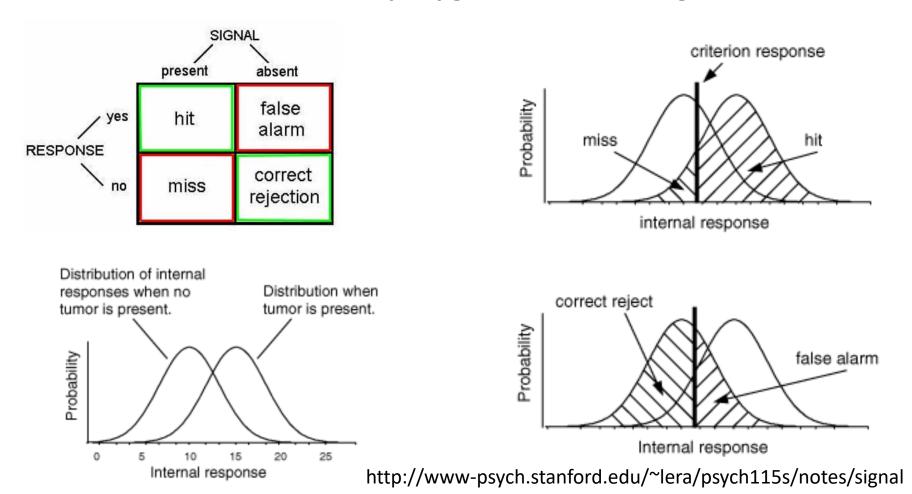


Two doctors, with equally good training, looking at the same CT scan, will have the same information ... but they may have a **different bias/criteria!**

How do you measure the quality in SDT?



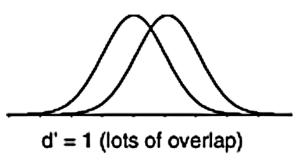
Remember: Two doctors, with equally good training, looking at the same CT scan data, will have the same information ... but they may gain different knowledge due to bias/criteria.

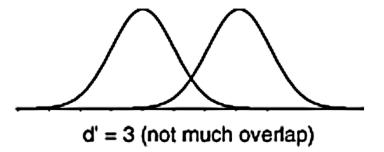


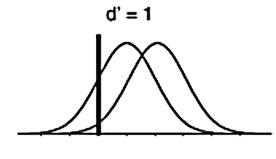
For an example see: Braga & Oliveira (2003) Diagnostic analysis based on ROC curves: theory and applications in medicine. *Int. Journal of Health Care Quality Assurance*, 16, 4, 191-198.

What does the Receiver Operating Characteristics tell?

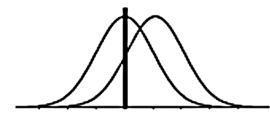




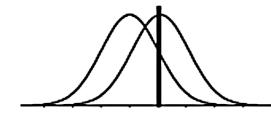




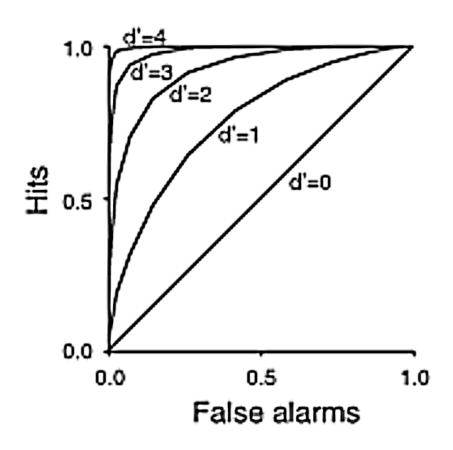
Hits = 97.5% False alarms = 84%



Hits = 84% False alarms = 50%



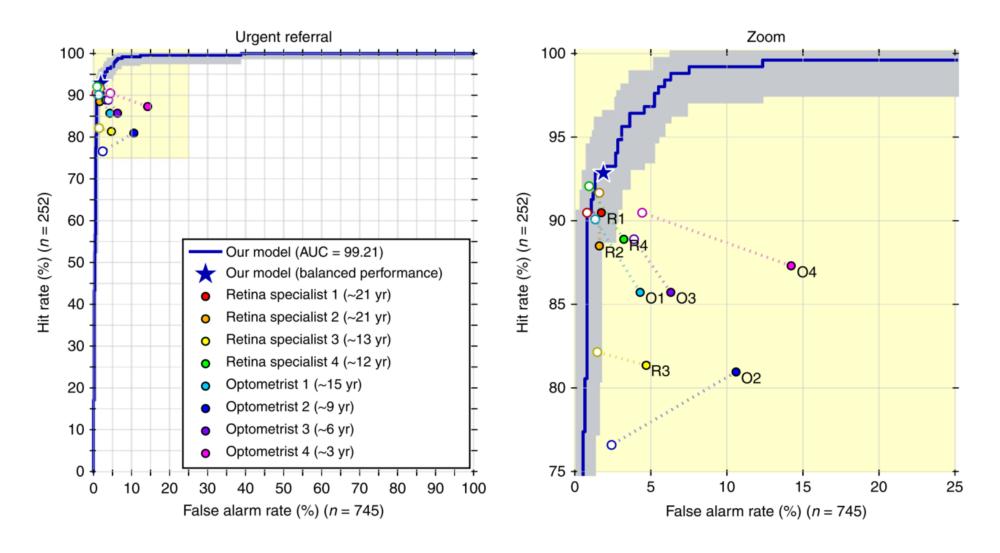
Hits = 50% False alarms = 16%



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

How do you measure Al performance?

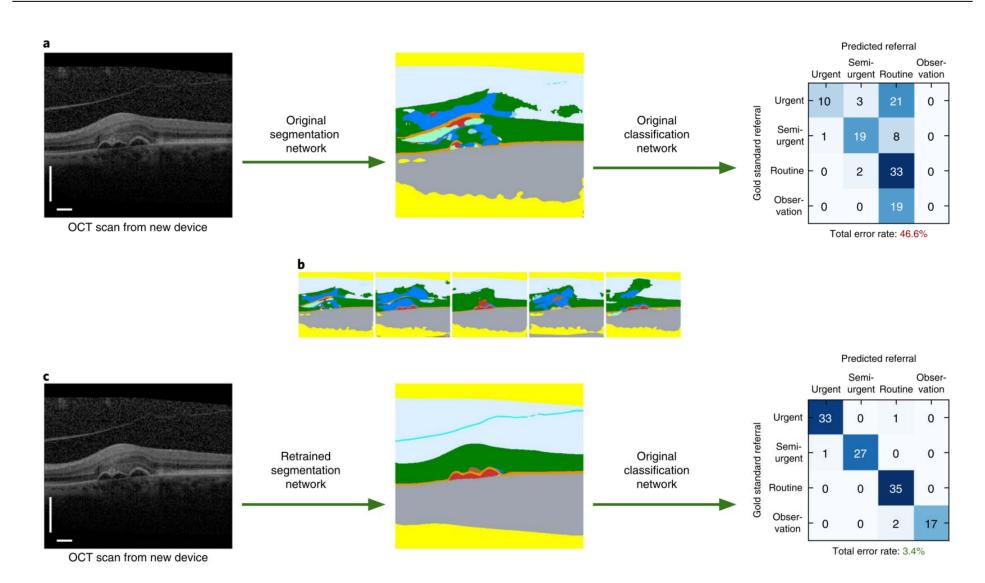




Jeffrey De Fauw et al. 2018. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature medicine*, 24, (9), 1342-1350

What is the confusion matrix showing you?





Jeffrey De Fauw et al. 2018. Clinically applicable deep learning for diagnosis and referral in retinal disease. *Nature medicine*, 24, (9), 1342-1350

What are Information acquisition and criteria bias?

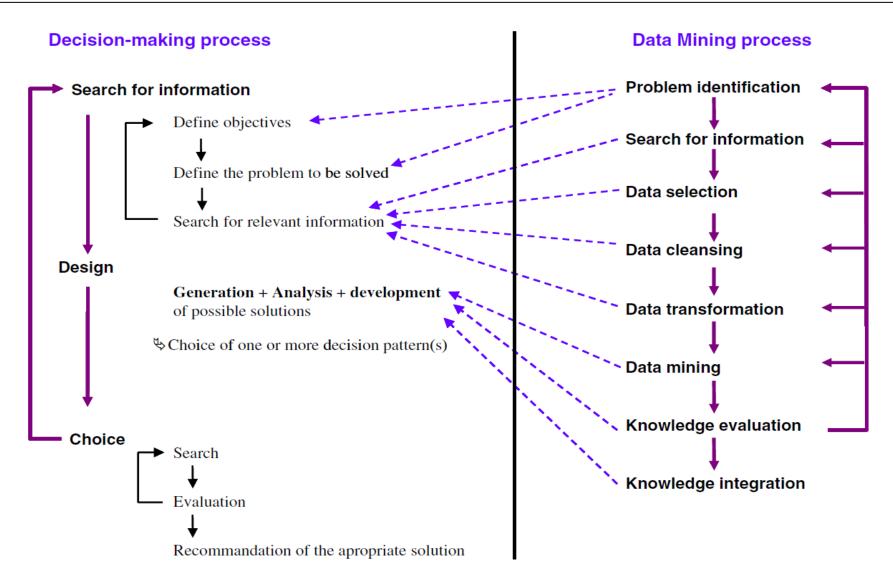


- **Information acquisition:** in the <u>CT data</u>, e.g. healthy lungs have a characteristic shape; the presence of a tumor might distort that shape (= anomaly).
- Tumors have different image characteristics: brighter or darker, different texture, etc.
- With proper training a doctor learns what kinds 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 (<u>relevant!</u>) 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.



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

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)

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

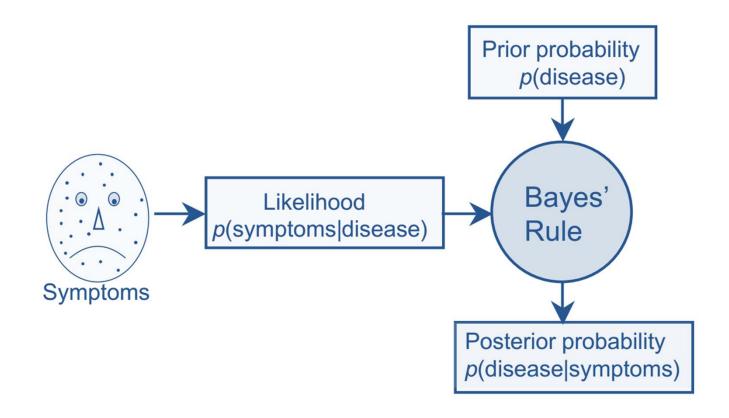
P(h | d): posterior (probability of hypothesis h after having seen the data d)

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

- 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



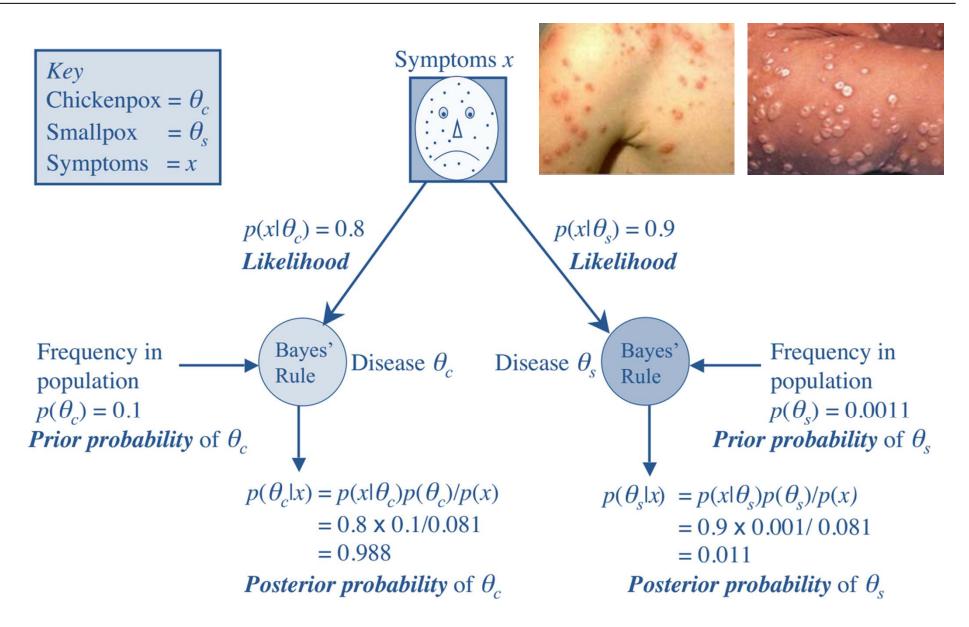


$$p(\text{disease}|\text{symptoms}) = \frac{p(\text{symptoms}|\text{disease})p(\text{disease})}{p(\text{symptoms})}$$

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

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

$$p(D = 1) = p(h) = 0,0001$$

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

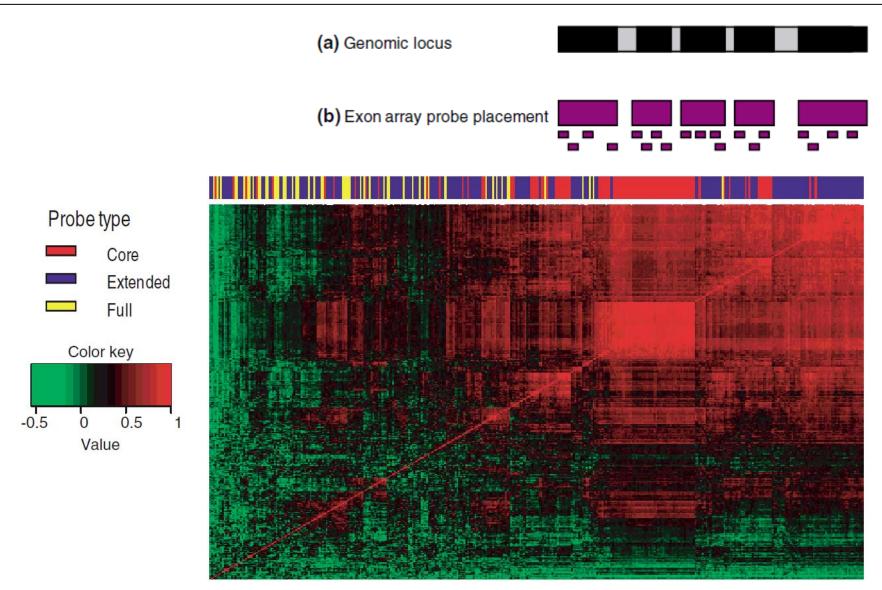
= 0,0098



05 Example:P4-Medicine

Example: Exon Arrays

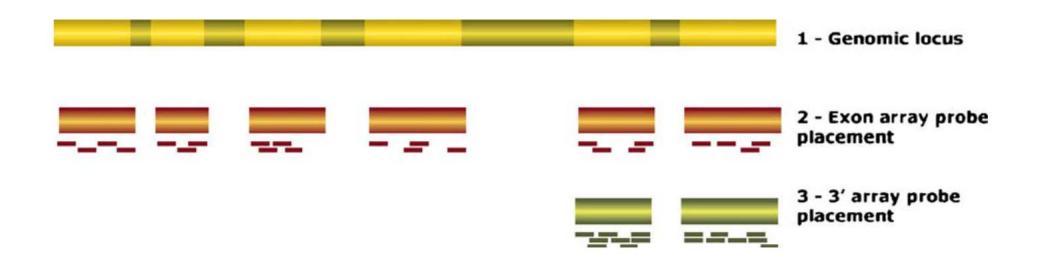




Kapur, K., Xing, Y., Ouyang, Z. & Wong, W. (2007) Exon arrays provide accurate assessments of gene expression. *Genome Biology*, 8, 5, R82.

Computational leukemia cancer detection 1/6



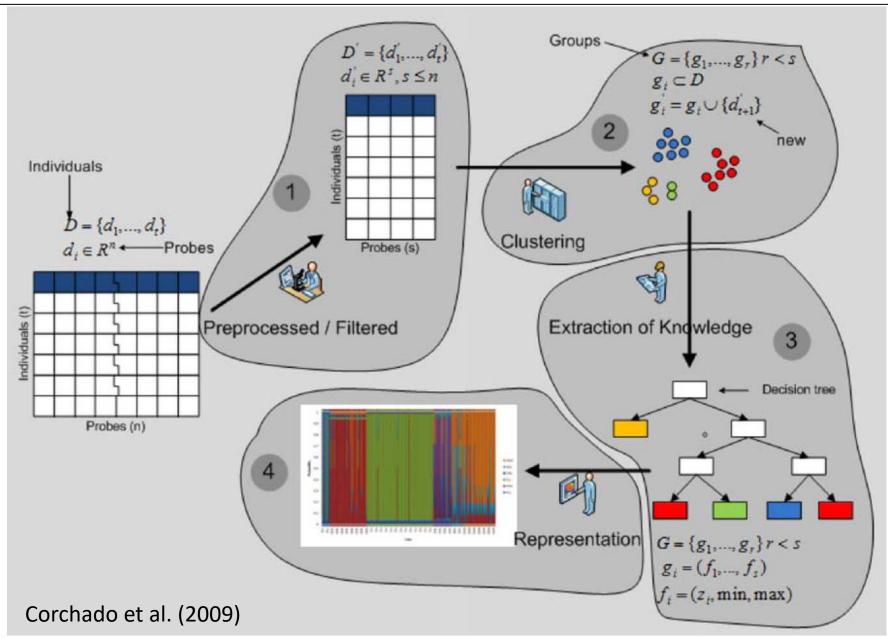


Exon array structure. Probe design of exon arrays. (1) Exon—intron structure of a gene. Gray boxes represent introns, rest represent exons. Introns are not drawn to scale. (2) Probe design of exon arrays. Four probes target each putative exon. (3) Probe design of 30expression arrays. Probe target the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

Computational leukemia cancer detection 2/6



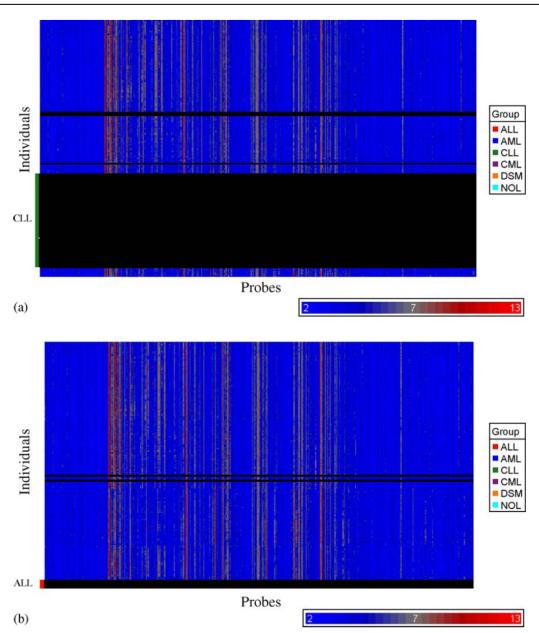


Computational leukemia cancer detection 3/6



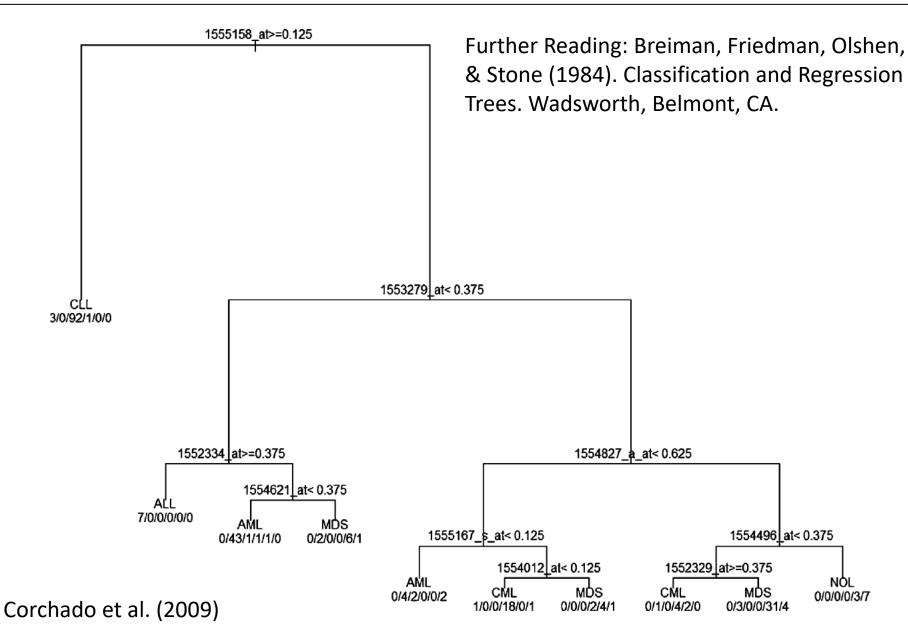
A = acute, C = chronic, L = lymphocytic, M = myeloid

- 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)



Computational leukemia cancer detection 4/6

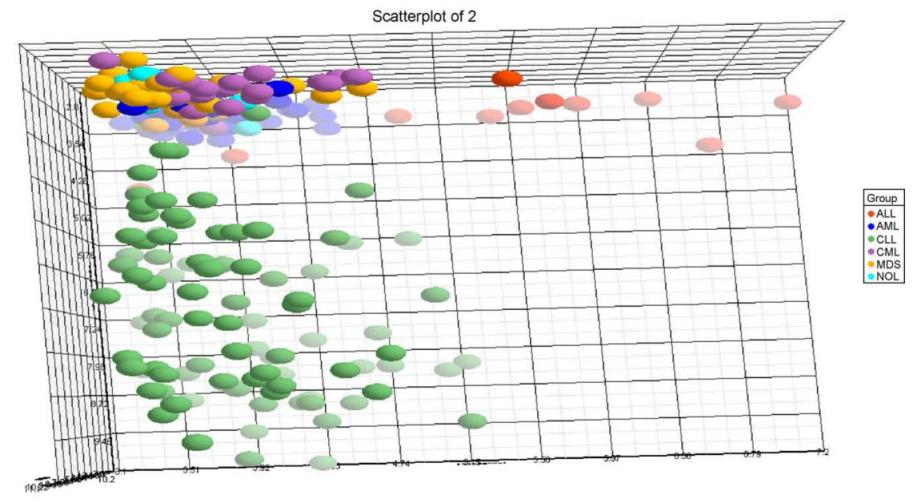




Computational leukemia cancer detection 5/6



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



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



06 Example: Case Based Reasoning (CBR)

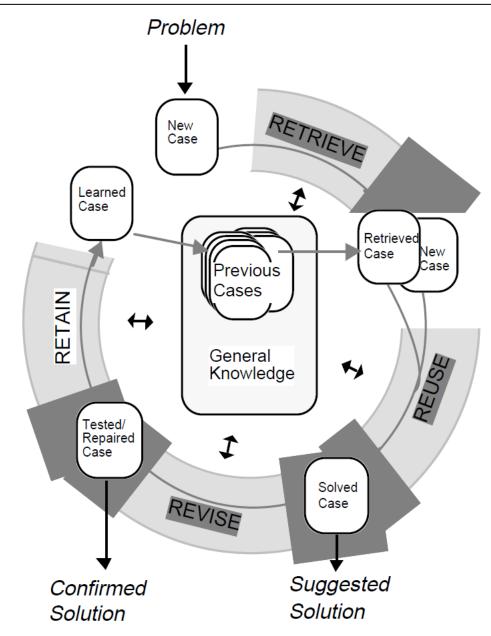
Thinking – Reasoning – Deciding – Acting





Case Based Reasoning (CBR) Basic principle

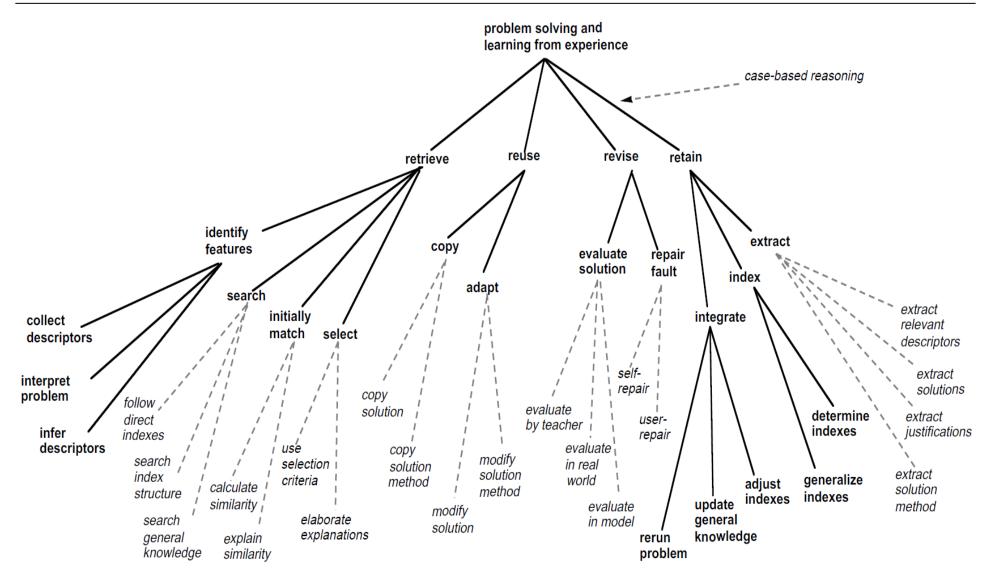




Aamodt, A. & Plaza, E. (1994) Case-based reasoning: Foundational issues, methodological variations, and system approaches. *AI Communications*, 7, 1, 39-59.

The task-method decomposition of CBR





Aamodt & Plaza (1994)

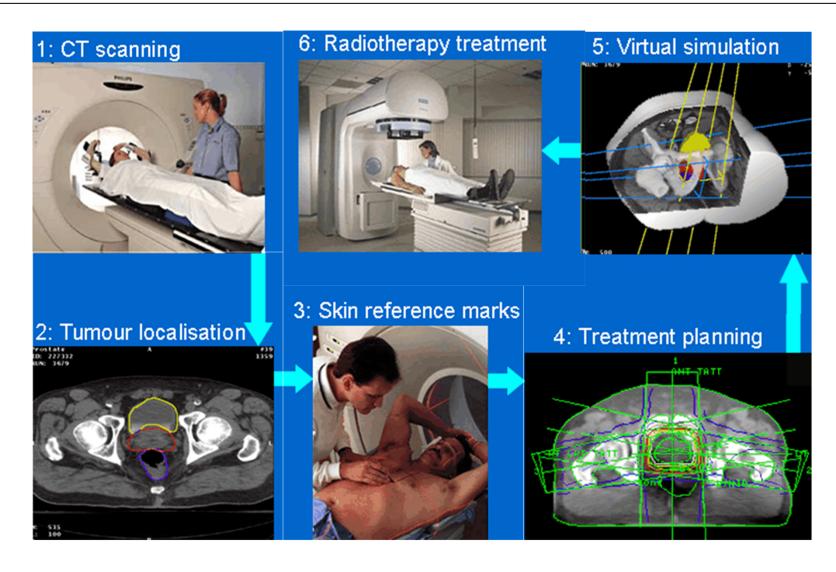
CBR Example: Radiotherapy Planning 1/6





CBR Example: Radiotherapy Planning 2/6

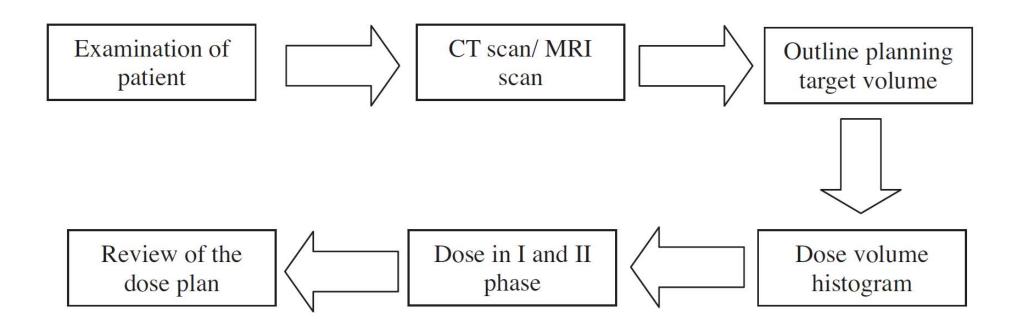




Source: Imaging Performance Assessment of CT Scanners Group, http://www.impactscan.org

CBR Example: Radiotherapy Planning 3/6





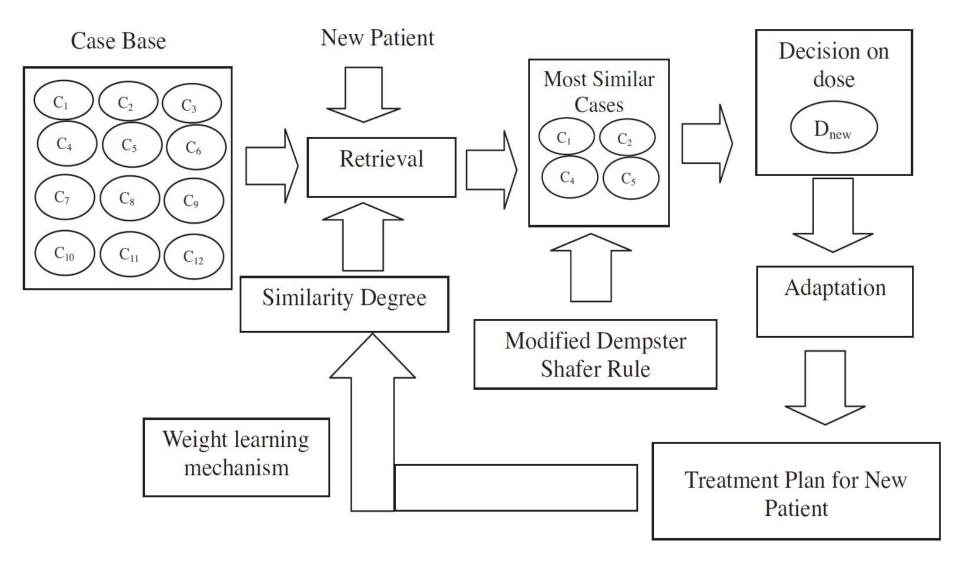
Measures:

- 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.

CBR System Architecture 4/6

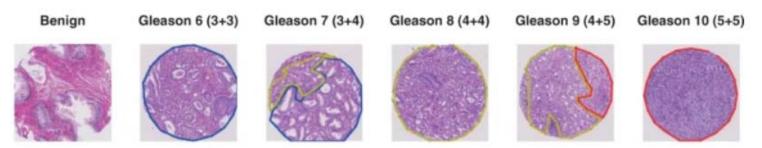




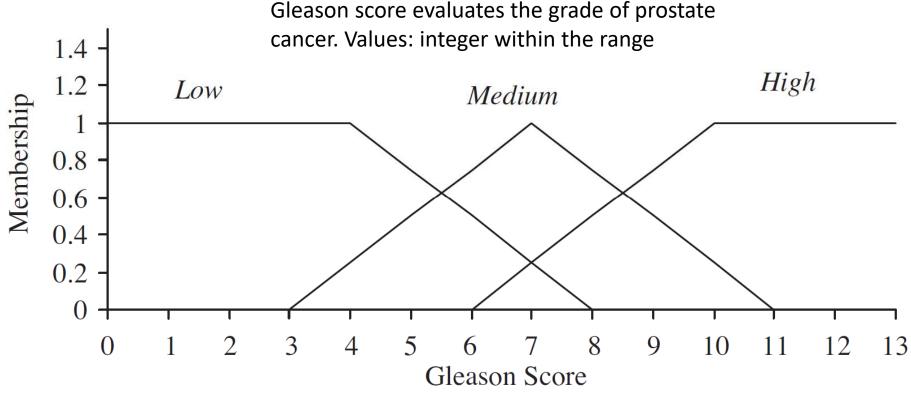
Petrovic, S., Mishra, N. & Sundar, S. (2011) A novel case based reasoning approach to radiotherapy planning. *Expert Systems With Applications*, *38*, *9*, *10759-10769*.

Membership funct. of fuzzy sets Gleason score 5/6





Eirini Arvaniti et al (2018). Automated Gleason grading of prostate cancer tissue microarrays via deep learning. Scientific Reports, 8, (1), doi:10.1038/s41598-018-30535-1.



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

Example: 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) Modification Feasible dose plan Proposed dose plan Yes No Modification of dose plan:

New dose plan: 62Gy +8 Gy

Dose received by 10% of rectum is: 54.26 Gy (feasible dose plan)



Conclusion



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..





Human vs. Computer



Human

sensitiveness for stimuli (visual, auditory, tactile, olfactory)

Ability for inductive Reasoning and complex Problem Solving

Creating of networked knowledge and storage for a live-long time

Flexibility in decisions, even in totally new situations

Discovering of ambiguous signals even when distorted

Computer

Precise Counting and Measuring of physical entities

Deductive Operations, formal Logic, Application of Rules

Storage of huge amounts of data which are not necessarily connected

Reliable reaction to unambiguous input signals

Reliable performance over long periods without tiredness

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



- 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



