Introduction to Decision Theory and Decision Analysis

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http://aragorn.wi.pb.bialystok.pl/~druzdzel/

Outline

- Introducing each other
- Organization of the course
- What is decision analysis?
- Contents of the course
- Course outline

The instructor

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WWW : http://aragorn.wi.pb.bialystok.pl/~druzdzel/

Who are you?

- What is your name, what do you want to be called?
- What is your educational background (prior studies, current program)?
- What is your professional background (prior and current work experience)?
- What can you do? What are your strengths?
- What is your dissertation topic?

Organization of the Course

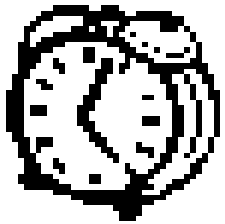
Objective of the course

The primary objective of this course is to make you acquainted with a set of tools for decision making under uncertainty known under the umbrella name of *decision analysis* and how these relate to building decision support systems.

I expect that you will learn:

- **How to use simple techniques for improving your own intuitive judgment and decision making under uncertainty.**
- **How to apply the tools of decision analysis to aid decision-making under uncertainty.**
- **How to employ decision-analytic methods in intelligent information systems and decision support systems.**

Meeting times



Classes (Room 237):

Wednesdays, 4:00-5:30pm

Marek's office hours (Room 136):

Wednesdays, 2:00-2:30pm or by appointment

Course materials

http://aragorn.wi.pb.bialystok.pl/~druzdzel/decision_theory.html

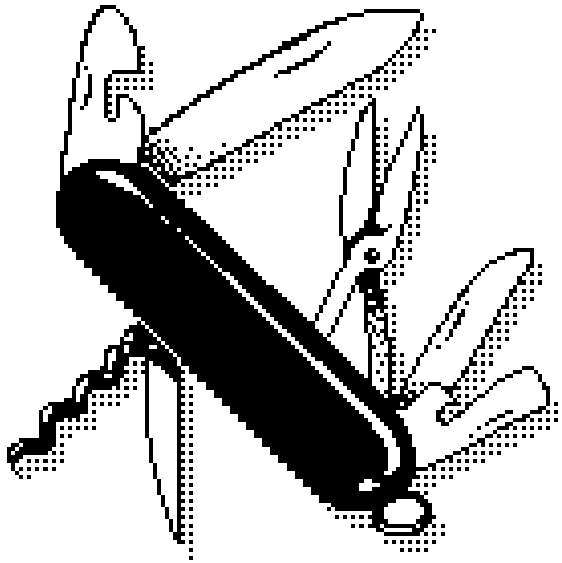
The above page is accessible from my home page at WI/PB:

http://aragorn.wi.pb.bialystok.pl/~druzdzel/

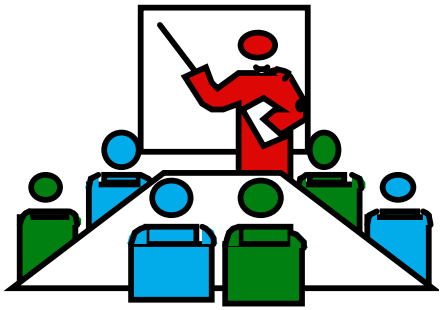
Grading

- **Project (formulation of the problem, presentation of the approach that will solve the presented problem; there is no point in dealing with something that will not be useful for you when working on your doctorate).**
- **The report should not be too long (5 pages?).**

Useful Advice (Hopefully)



Come to our meetings …
... and be their active participant



- Being there is important.
- Our in-class discussions and exercises will play a role in your learning.
- Understanding difficult parts of the material on your own may often cost you a multiple of what it takes in class.

Do not hesitate to ask questions, interrupt me if needed

… and be their active participant

- This is the best way to learn
- Do not hesitate to ask questions, interrupt me if needed

What is Decision Analysis?

What is a good decision?

As many good questions, this question does not have a crisp-cut answers ☺.

Can you judge decisions by their outcomes?

The story of Bill and Bob

What is a good decision then?

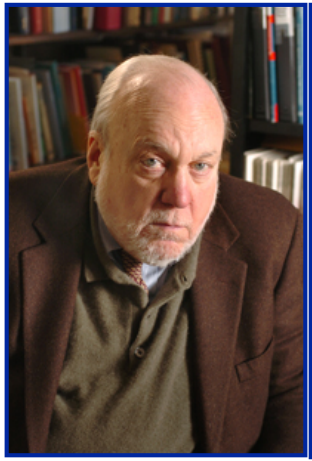
One possible answer:

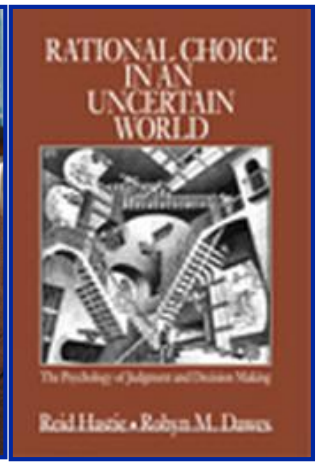
- One that results from a good decision making process
- Improving decisions means mostly improving the decision-making process.
- A nice criterion for good decisions is to "look forward and back.“ Imagine yourself in the future, looking back at your own decision now. Will you be able to say regardless of the outcome: "Given everything I knew at that time — and I did a pretty good job of digging out the important issues — I made the appropriate decision. If I were put back in the same situation, I would go through the process pretty much the same way and would probably make the same decision." If your decision making lets you say this, then you are probably making good decisions.
- The issue is not whether you can foresee some unusual outcome that really is unforeseen, even by experts. The issue is whether you carefully consider the aspects of the decision that are important and meaningful to you.

Decisions, decisions …
(or Human Decision Making Under Fire)

Decades of laboratory work demonstrating that we are not too good in judgment and decision making ☹

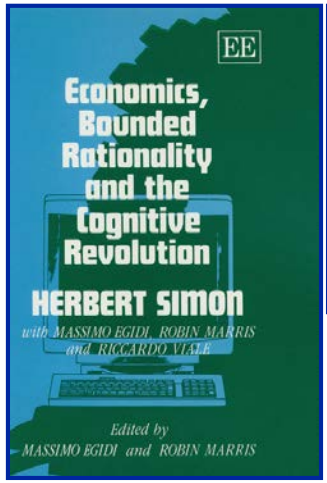
My favorites

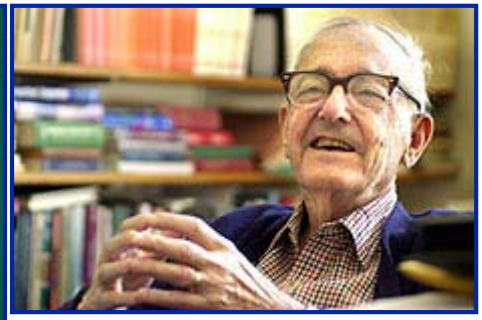




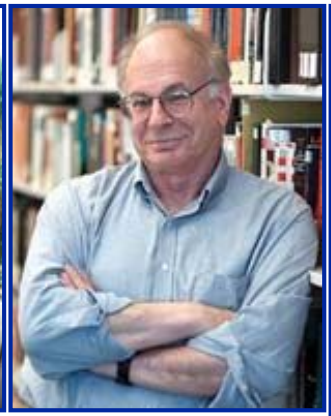
http://archive.constantcontact.com/fs014/1102665924422/archive/1107391946021.html

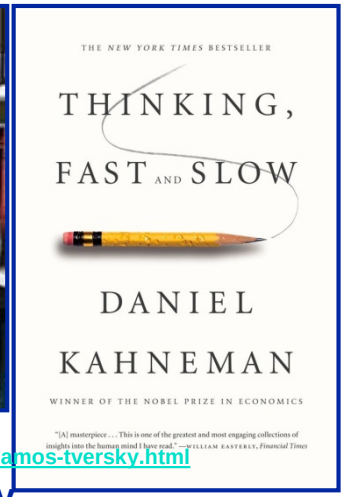
Robyn Dawes





Herb Simon





http://grawemeyer.org/psychology/previous-winners/2003-daniel-kahneman-and-amos-tversky.html

Daniel Kahneman and Amos Tversky

But how do we do in real life? College admissions

Admissions committee in University of Oregon's Psychology Department and proper and improper linear models were compared to faculty ratings of students 2 to 5 years after matriculation.

Observed correlations:

- **0.19 with the admissions committee**
- **0.38 with proper model (half sample)**
- **0.48 with improper model (weights 1.0 and -1.0)**

http://www.calu.edu/current-students/new-student-resources/index.htm

But how do we do in real life? Medical school admissions

University of Texas medical school. The admissions process has two steps. First, all applicants are screened for likelihood for academic success; criteria include academic performance, assessment by advisers, etc. Second, applicants who meet the criteria are interviewed; those with the best rankings are accepted.

In 1979, 150 students were selected. Afterwards, 50 more had to be accepted from those who had been interviewed but rejected.

This gave an excellent opportunity (an experimental setup!) to compare the performance of medical students who had been initially accepted and initially rejected. It turned out that there was no meaningful difference in performance between both groups.

The interview process does not seem to be worthwhile as a predictive tool.

http://dukeeyecenter.duke.edu/modules/eyectr_student/index.php?id=5

But how do we do in real life? Prediction of violent behavior of psychiatric patients

A simple model that looked at past instances of violent behavior in psychiatric patients performed better than a panel of psychiatrists in predicting future violent behavior.

http://boards.weddingbee.com/topic/new-dress-designs-for-mother-in-laws#axzz2Lx28EtHt

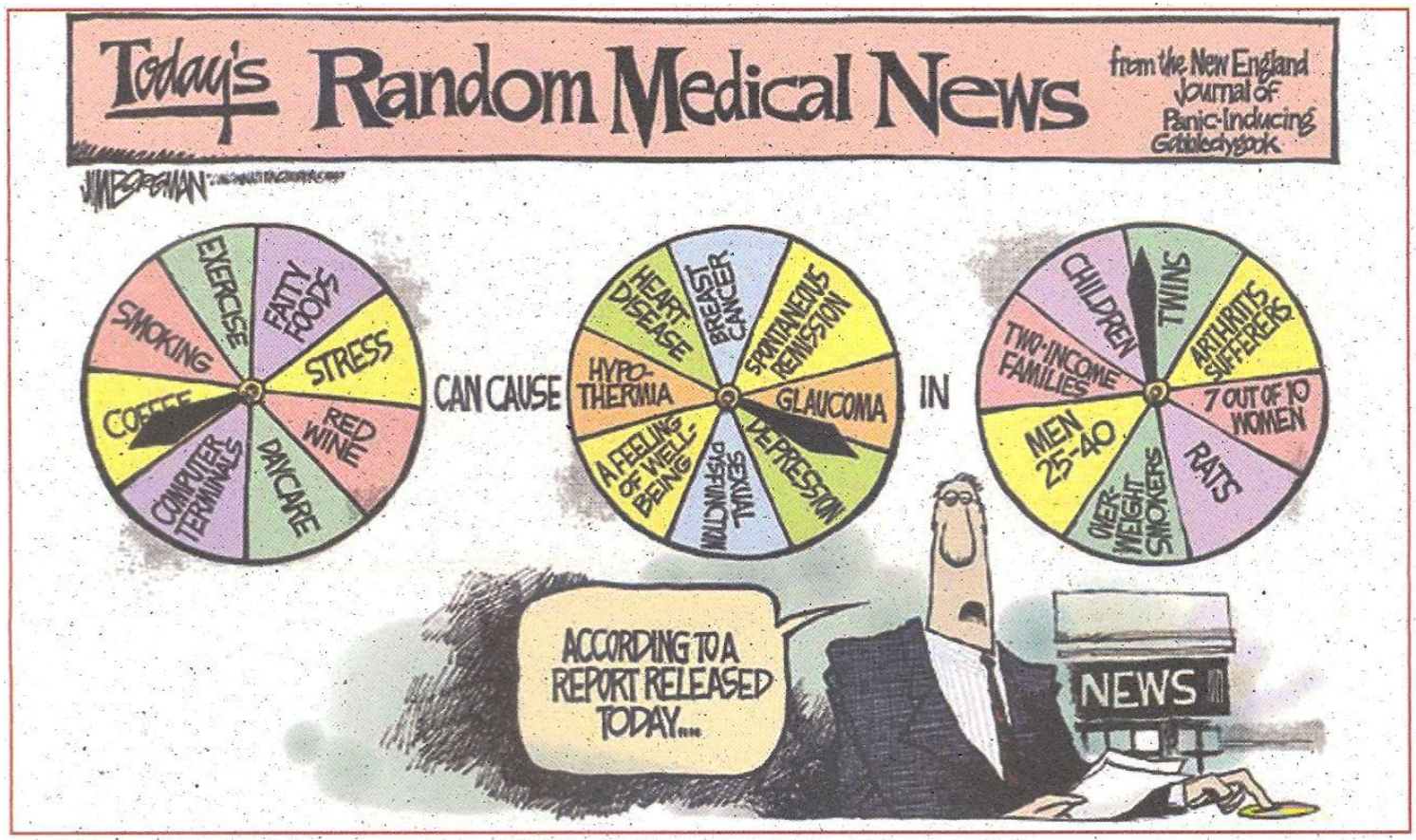
But how do we do in real life? Prediction of marital happiness

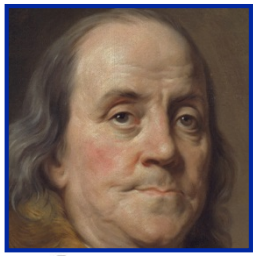
A simple model that subtracted the average number of fights a week from the average number of incidences of sexual intercourse a week performed better than marital therapists

http://articles.chicagotribune.com/2013-04-09/features/sc-fam-0409-marriage-counselor-20130409_1_couples-therapy-relationship-counseling/

http://www.justinstum.com/marriage-and-couples-counseling-in-st-george/

Where does the difficulty come from?



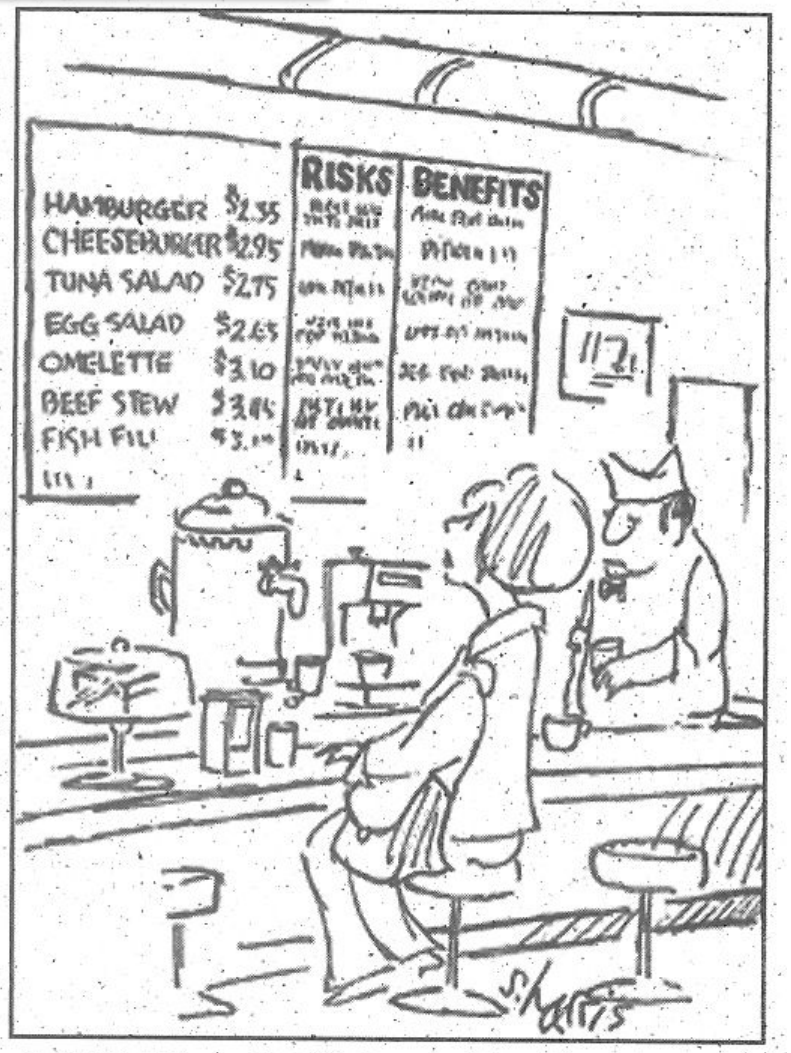


"*... in this world nothing can be said to be certain, except death and taxes*" –Benjamin Franklin in a letter to his friend M. Le Roy

(*) *The Complete Works of Benjamin Franklin*, John Bigelow (ed.), New York and London: G.P. Putnam's Sons, 1887, Vol. 10, page 170

Where does the difficulty come from?

- Complexity
- Conflicting objectives
- Many decision alternatives

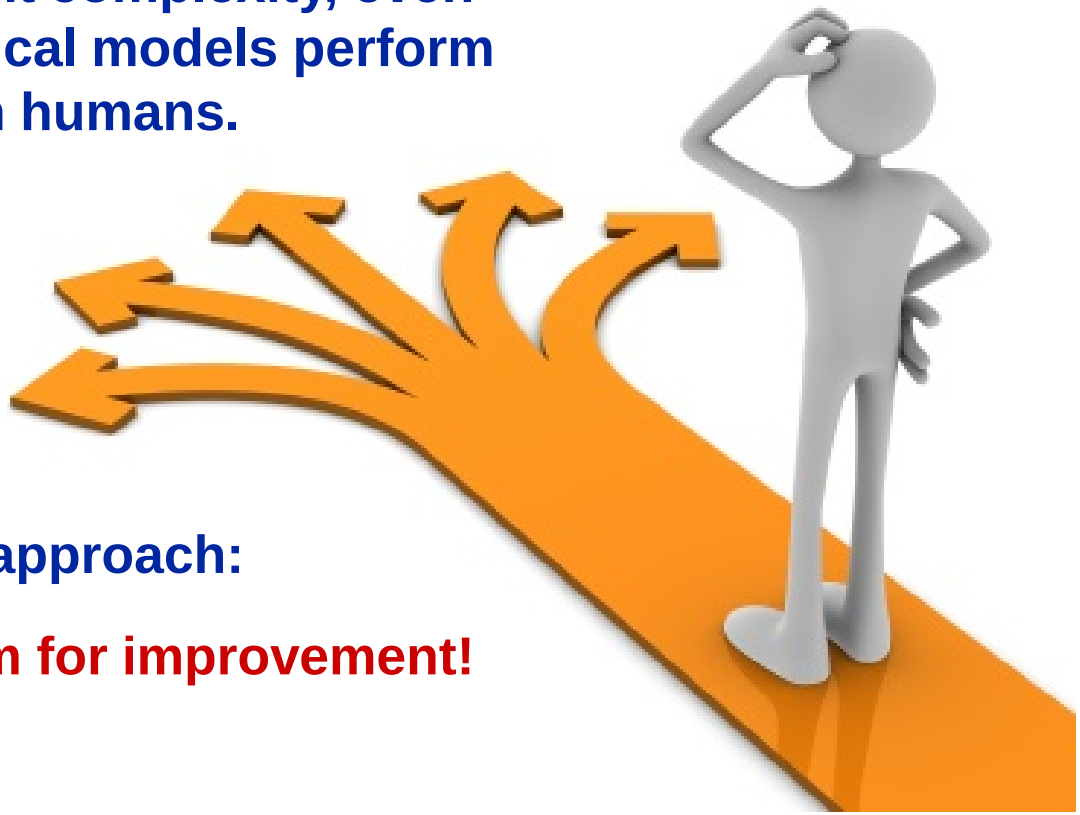


Where does the difficulty come from?

- Multiple decision makers and their perspectives
- Our cognitive limitations
- High stakes
- Time pressure

Human decision making

(In most tasks requiring analytical thinking,) in situations of sufficient complexity, even the dumbest mathematical models perform consistently better than humans.



"The glass is half-full" approach:

There is a lot of room for improvement!

http://www.jessicasimien.com/whit-wisdom-make-a-decision/

Elements of Decision Analysis

Decision support

Are people good at decision making?

A similar question:

Are people good at arithmetics?

Why not use a calculator ☺?

http://www.abcteach.com/directory/clip-art-math-4125-2-1

Decision theory and decision analysis


John von Neumann & Oskar Morgenstern

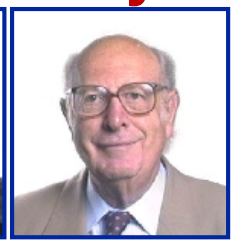
Decision theory (1920s-1930s):

A mathematical theory of how decisions should be made

(based on the idea that uncertainty and preferences should combine like mathematical expectation)

Decision analysis (1960s+):

The art and craft of applying decision theory in practice

Ronald Howard Howard Raiffa

Decision Analysis

Challenge:

Identify what people are good at and support what they don't do too well

- It seems that people are much better at selecting and coding information (what to look for, what factors to consider) than they are at integrating it.
- This is a fundamental assumption of decision analysis, but one that has been verified in practice by numerous studies.
- Decision analysis is an aid to human decision making, just as a calculator is an aid to our limited capability for mental arithmetic.

Elements of decisions

Decisions are made everywhere, including science. What are their elements?

- **Preferences (a.k.a. objectives)**
- **Actions (a.k.a. decision options)**
- **Uncertainty (nuisance but, unfortunately a fact of life ☹)**

Other relevant concepts:

- **Context of a decision (situation)**
- **Consequences (outcomes)**
- **Dynamic character of decision problems (often leads to sequential decisions)**

The goal of decision analysis

Insight not numbers!

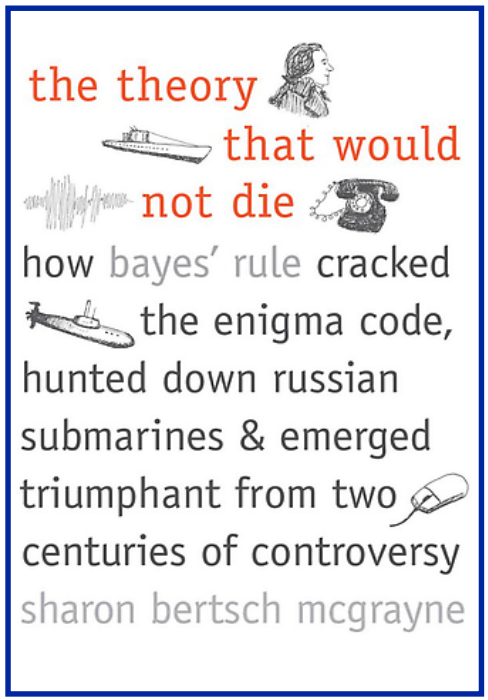
- Decision analysis provides structure and guidance to thinking systematically about hard decisions
- A DA exercise will be successful if the decision maker has learned something about the problem
- Sometimes it offers justification of previously made choices, but even then it is useful by offering insight

Normative vs. descriptive decision support

- Traffic laws vs. actual behavior of drivers
- Bible vs. actual behavior of people

Bayes theorem and Bayesian statistics

A versatile and powerful theory that seems to solve a variety of problems, originating from an 18th century English mathematician, Rev. Thomas Bayes (http://en.wikipedia.org/wiki/Thomas_Bayes)



Bayes Theory is so "hot" that a lightly written book "The Theory That Would Not Die," published in 2011, has become a bestseller

Recommended video:
http://www.youtube.com/watch?v=8oD6eBkjF9o

Bayesian modeling is reliable and it solves hard problems.

It can use both, data and expert knowledge.

What is the relation of Bayesian statistics to classical statistics?

What is $p($  $)$?

Classical statisticians: “We have no clue ☹. Probability is a limiting frequency. A nuclear war is not a repetitive process.”

Bayesians: “0.24 ☺. Probability is a measure of belief”

“Immeasurables”

Some things are difficult to express in numerical terms.

Imagine that you are a juror. How much is it worth to condemn an innocent man or to release a guilty one?

How do you judge money vs. health or happiness?

The need for utility

Even if you can express “immeasurables” in numbers, there are problems with expected value, found quite a while ago (even though probability is quite young).

Bernoulli (17th century) pointed out these problems and the need to have some measure of preferences.

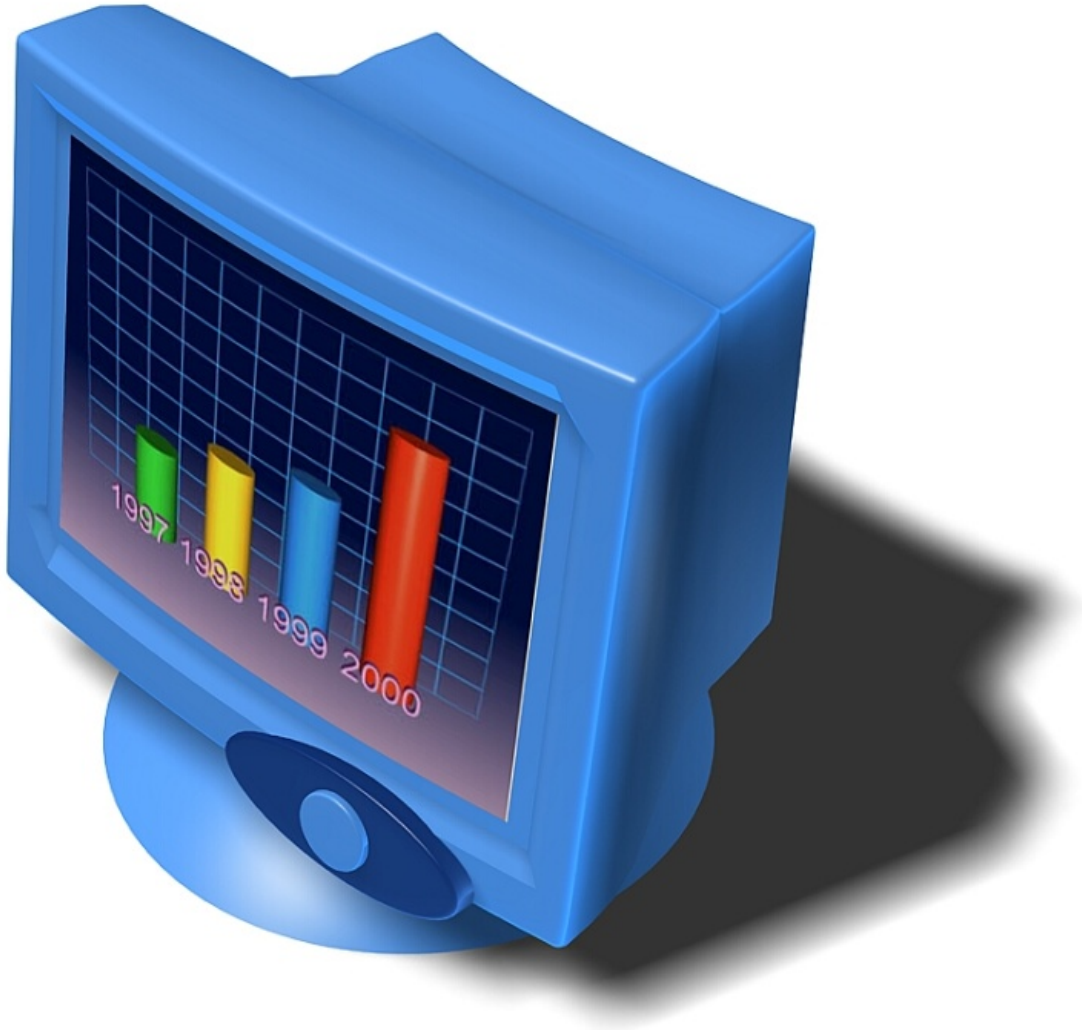
Then there was long nothing, just a qualitative, ordinal notion (note the gymnastics around qualitative notion of utility in economics) and finally a quantitative, cardinal utility in 1940s due to von Neuman & Morgenstern.

Applications

Numerous!

- Medical diagnosis, prognosis, therapy planning
- Fraud detection
- Machine diagnosis and prognosis (in the context of machine maintenance)
- Diagnosis of database servers
- Diagnosis of airplanes, diesel locomotives, IC “baking” devices
- Data analysis
- Strategic planning
- …

Software demo



- Simple models
- Diagnostic applications
- Learning
- Qualitative models
- Dynamic models
- Equations

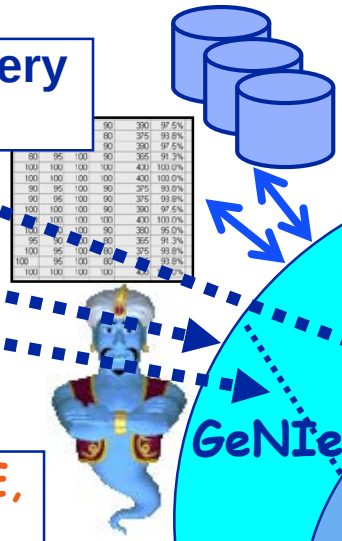
GeNIe

A developer's environment for graphical decision models (https://www.bayesfusion.com/).

Qualitative interface: QGeNIe

Learning and discovery module: SMiner

Diagnosis: Diagnosis



Model developer module: GeNIe.

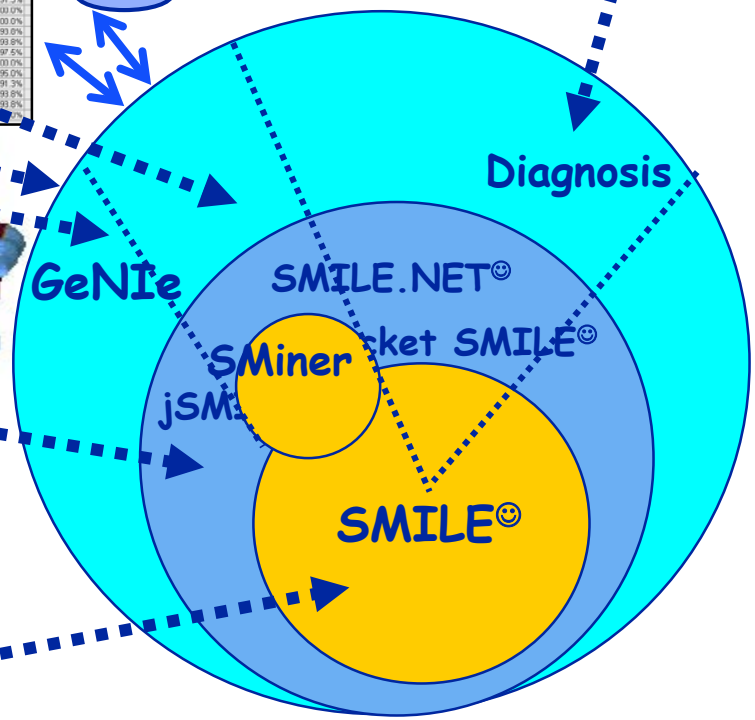
Implemented in Visual C++ in Windows environment.

Wrappers: SMILE.NET jSMILE, rSMILE, PySMILE, SMILE.COM, Pocket SMILE

Allow SMILE© to be accessed from applications other than C++compiler

Reasoning engine: SMILE© (Structural Modeling, Inference, and Learning Engine).

A platform independent library of C++ classes for graphical models.



Learning/Data Mining

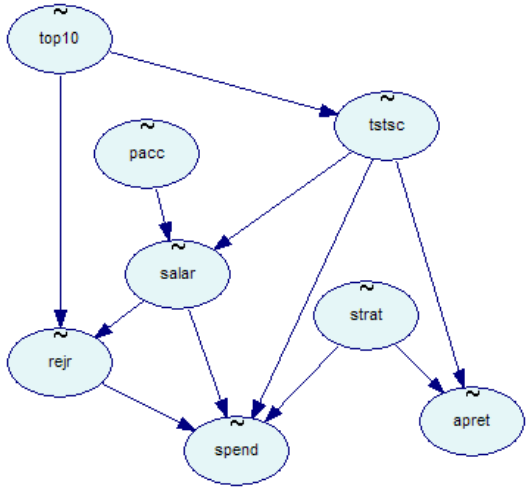
GeNIe/SMILE© have the capability to analyze data, discover causal patterns in them, and build models based on these data.

Retention.txt

spend	apret	top10	rejr	tstsc	pacc	strat	salar
9855	52.5	15	29.474	65.063	36.887	12	60800
10527	64.25	36	22.309	71.063	30.97	12.8	63900
7904	37.75	26	25.853	60.75	41.985	20.3	57800
6601	57	23	11.296	67.188	40.289	17	51200
7251	62	17	22.635	56.25	46.78	18.1	48000
6967	66.75	40	9.718	65.625	53.103	18	57700
8489	70.333	20	15.444	59.875	50.46	13.5	44000
9554	85.25	79	44.225	74.688	40.137	17.1	70100
15287	65.25	42	26.913	70.75	28.276	14.4	71738
7057	55.25	17	24.379	59.063	44.251	21.2	58200
16848	77.75	48	26.69	75.938	27.187	9.2	63000
18211	91	87	76.681	80.625	51.164	12.8	74400
21561	69.25	58	44.702	76.25	26.689	9.2	75400
20667	65	68	22.995	75.625	28.038	11	66200
10684	61.75	26	8.774	66	33.99	9.5	52900
11738	74.25	32	25.449	66.875	27.701	12	63400
10107	74	43	11.315	71	29.096	16.2	66200
7817	65.75	36	33.709	64.25	52.548	17.7	54600
7050	26	11	0	55.313	55.651	18.8	59500
9082	83.5	73	64.668	77.375	43.185	13.6	66700
11706	60	56	16.937	73.75	39.479	12.7	62100
7643	49.25	23	36.635	62.813	39.302	18.7	57700
25734	90	77	67.758	80.938	44.133	10	80200
20155	86	84	69.31	79.688	48.766	17.6	74000
29852	94.5	84	75.009	81.313	51.363	10.6	74100
7980	68.5	34	9.122	63.875	35.294	16.3	53100

Row 1 of 170

data



causal structure

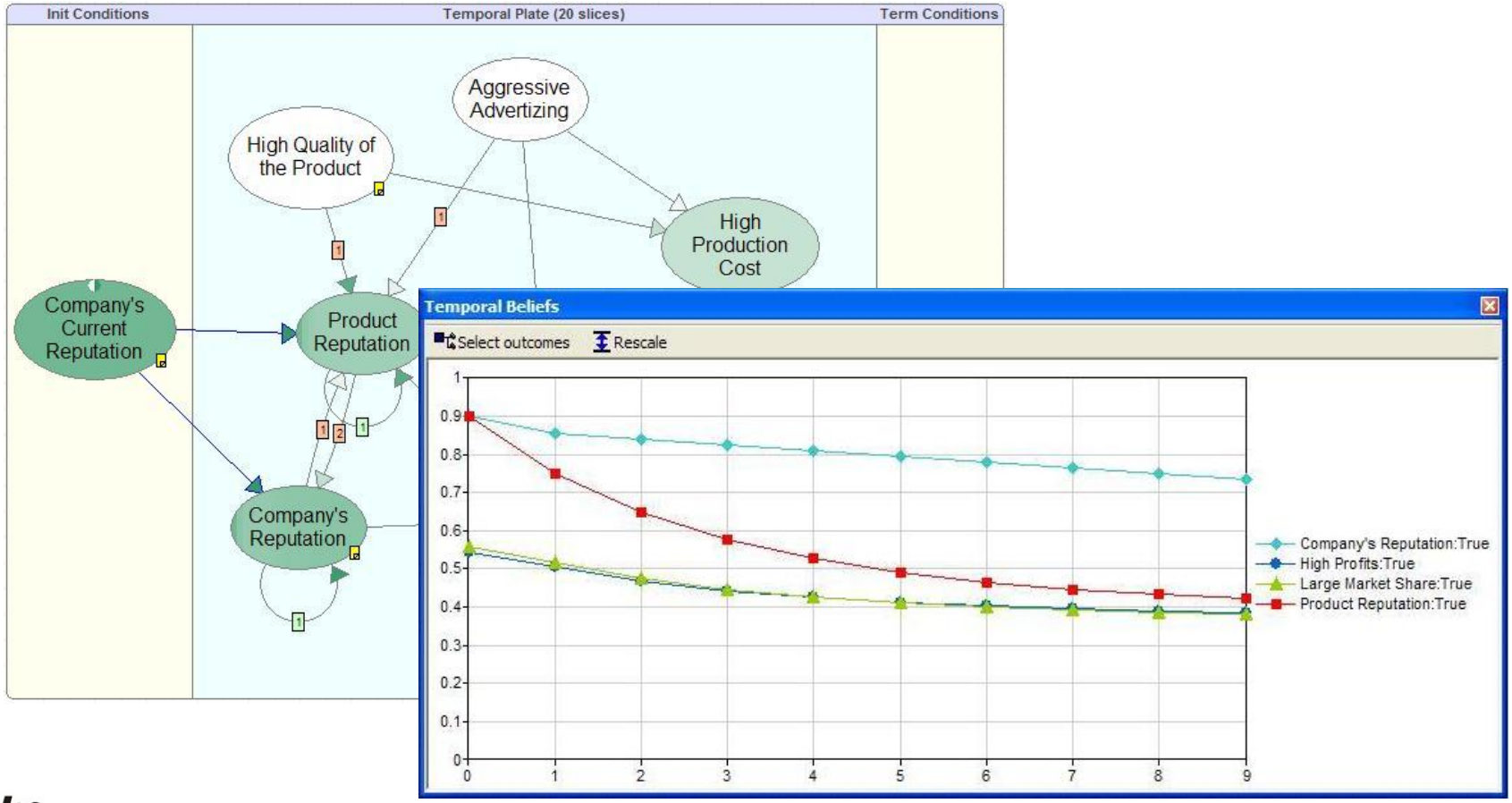
Success	0.2
Failure	0.8

Success	Success	Failure
Good	0.4	0.1
Moderate	0.4	0.3
Poor	0.2	0.6

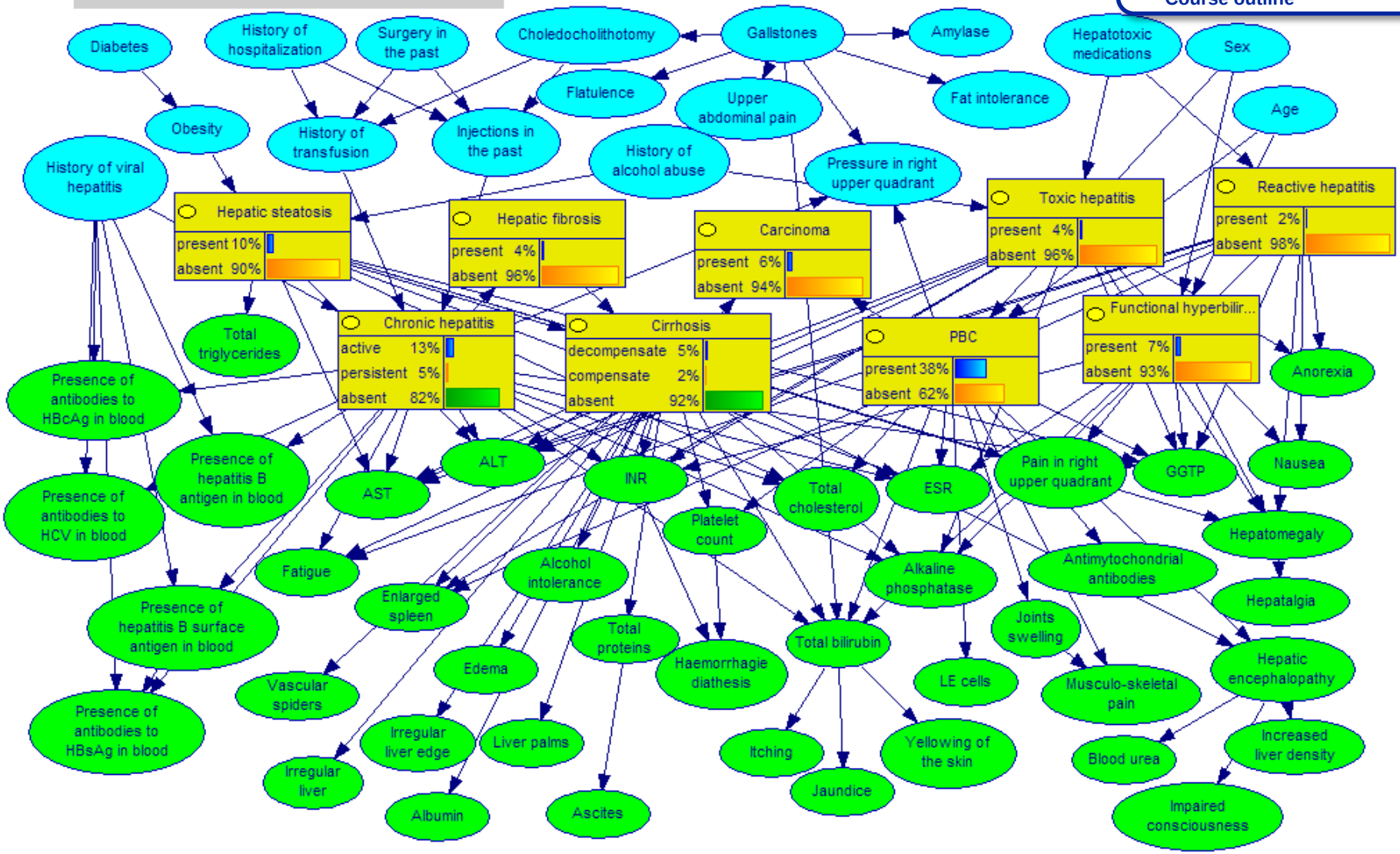
numerical parameters

Temporal reasoning

Temporal models allow for tracking development of a system over time and support decision making in complex environments, where not only the final effect counts.

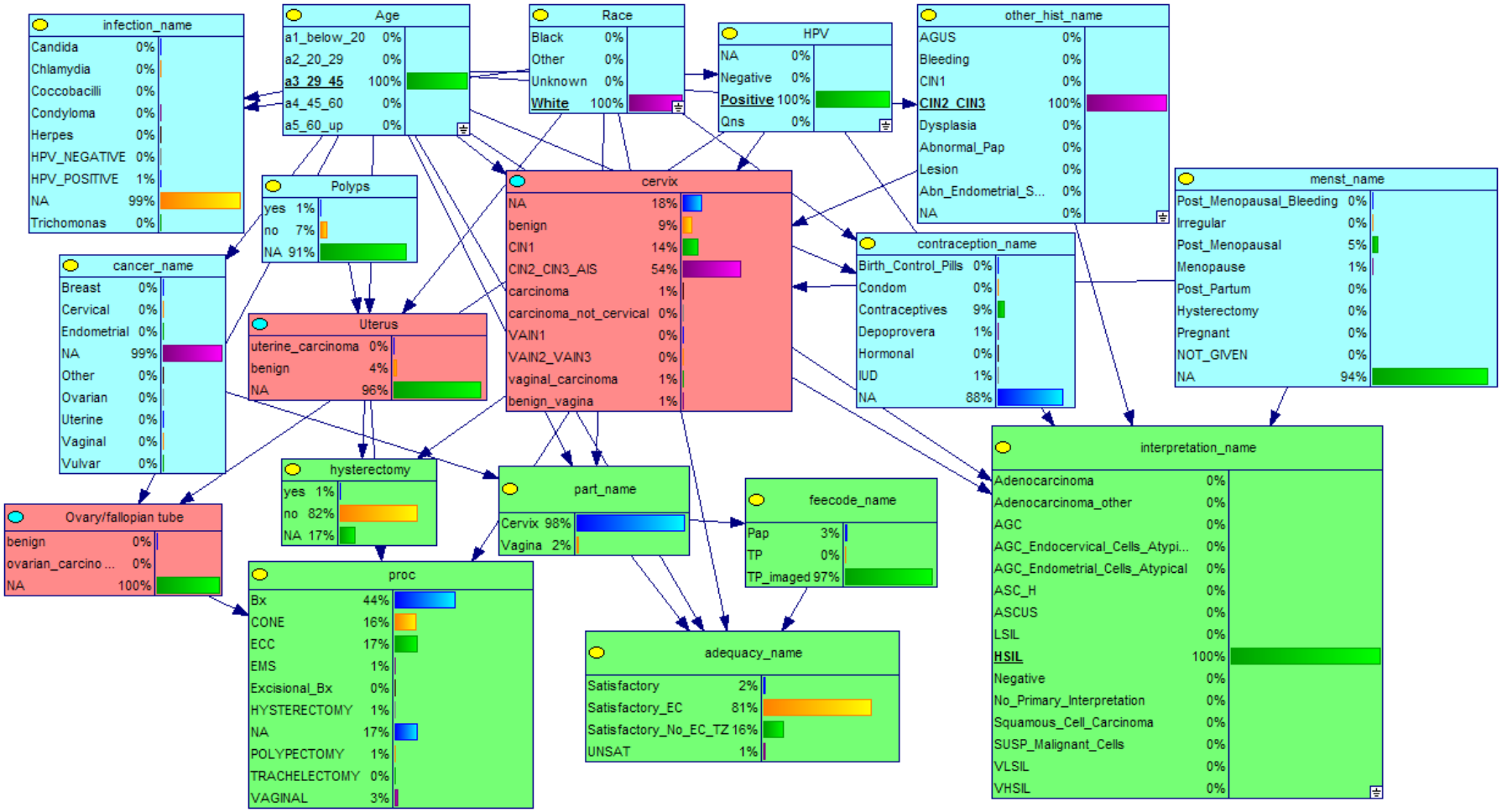


HEPAR II Model



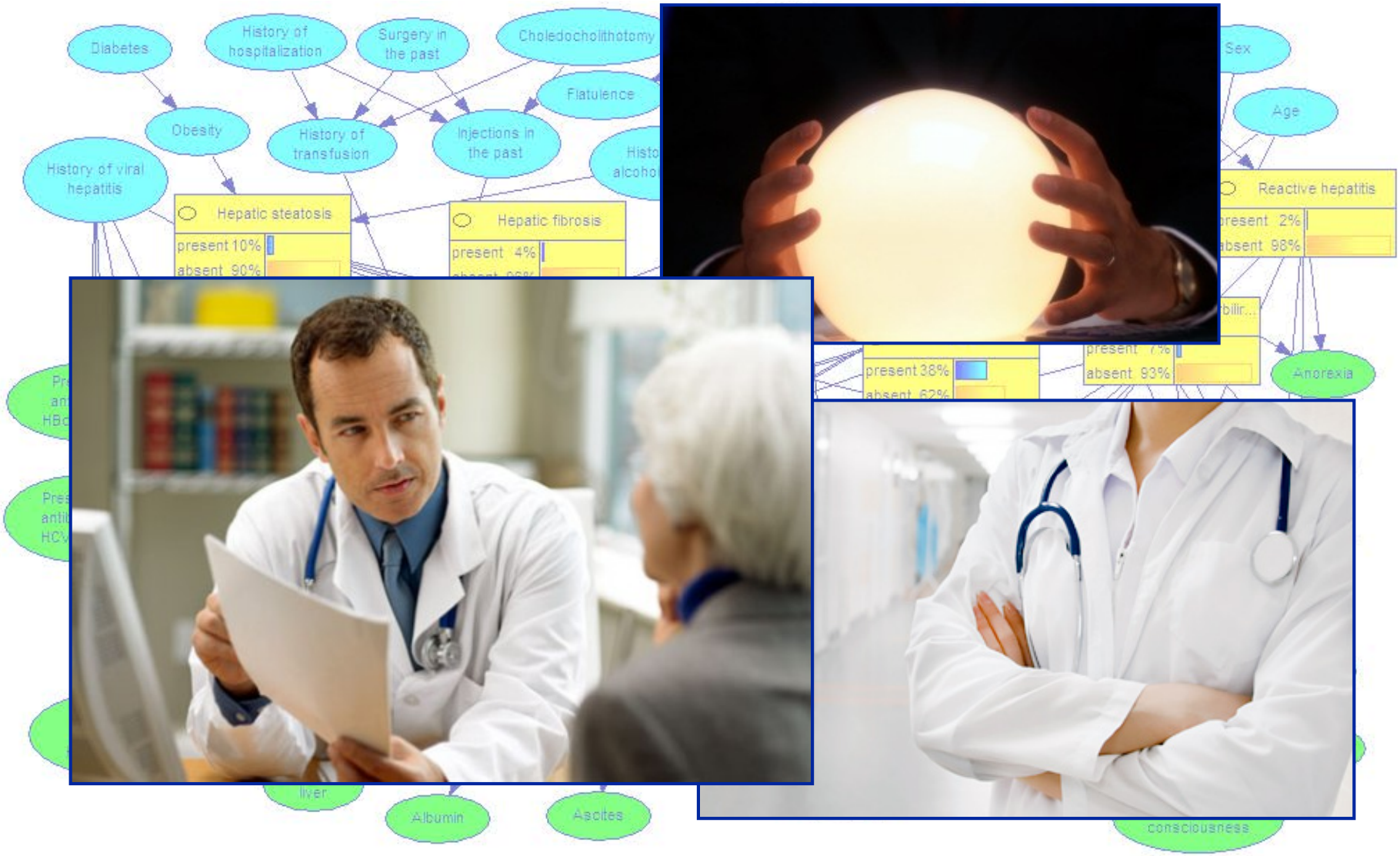
70 variables; 2,139 numerical parameters (instead of over $2^{70} \approx 10^{21}$!)

Pittsburgh Cervical Cancer Screening Model



[Oniśko et al.] 18 variables; 295,163 numerical parameters

Diagnosis, prediction, prognosis

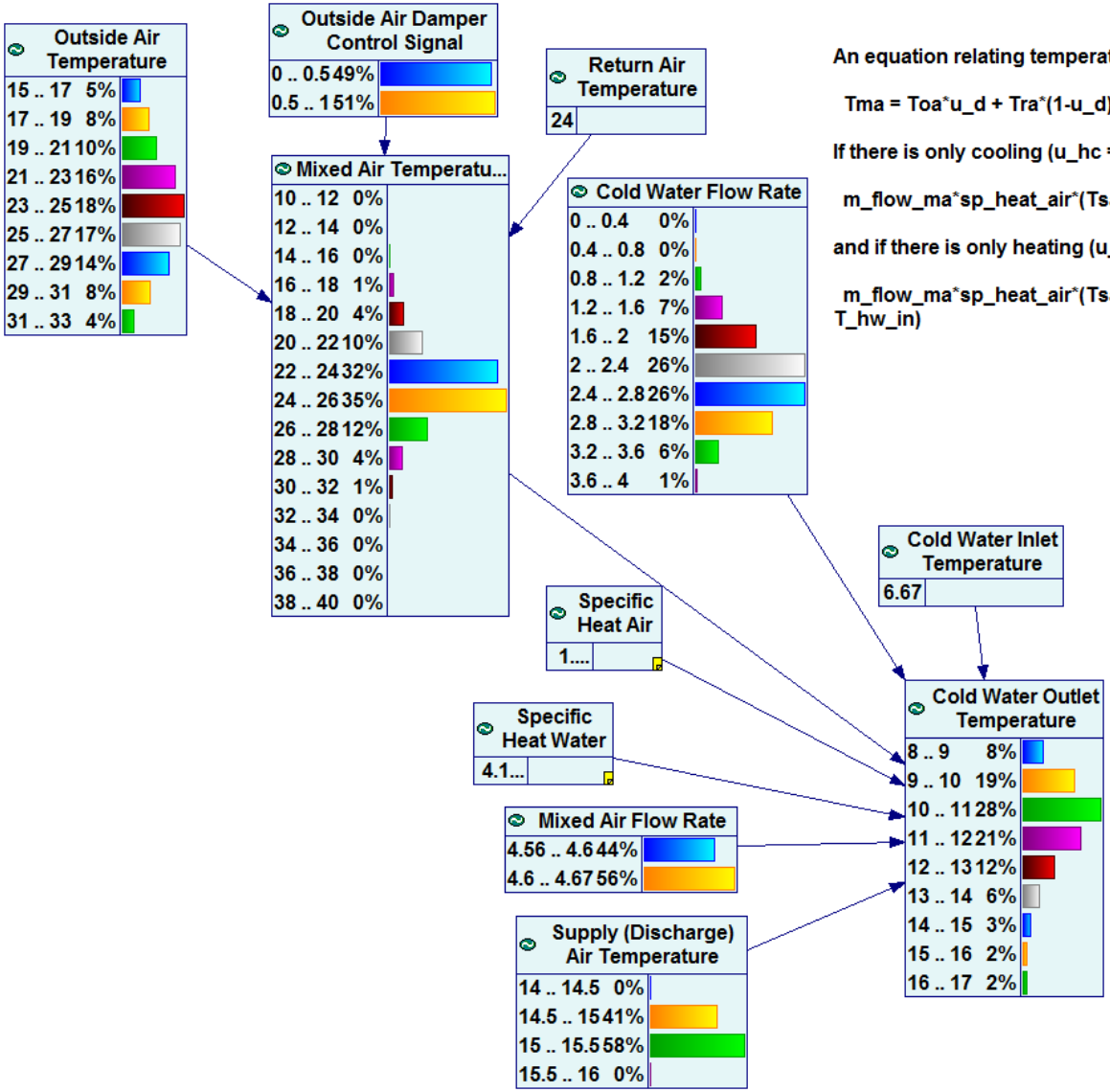


Symptomate: An intelligent medical consultant

http://www.doktor-medi.pl/
http://www.symptomate.com/
http://dxmate.com/

https://symptomate.com/

Modeling engineering and financial processes



An equation relating temperatures before and after the damper:

$$Tma = Toa*u\_d + Tra*(1-u\_d)$$

If there is only cooling (u_hc == 0)

$$m\_flow\_ma*sp\_heat\_air*(Tsa - Tma) = mdot\_cw*sp\_heat\_water*(T\_cw\_out - T\_cw\_in)$$

and if there is only heating (u_cc ==0)

$$m\_flow\_ma*sp\_heat\_air*(Tsa - Tma) = mdot\_hw*sp\_heat\_water*(T\_hw\_out - T\_hw\_in)$$

Detection

- Spam detection
- Fraud detection
- Detection of conflicting medicine

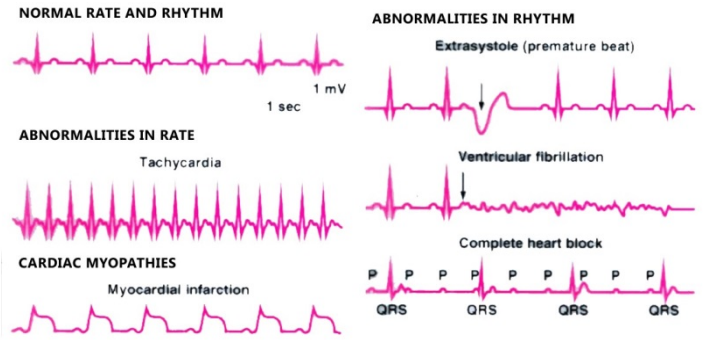
http://sciencebasedpharmacy.wordpress.com/tag/drug-regulation/

http://californialoanfind.com/what-and-who-is-teletrack/

Recognition

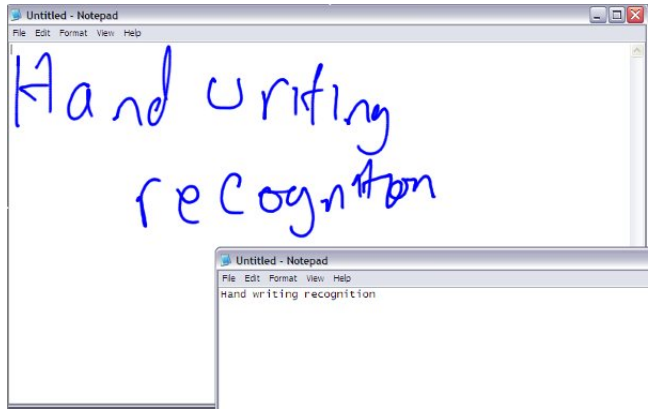
- Handwriting recognition
- Face recognition
- Optical character recognition
- Pattern recognition
- Speech recognition

http://www.stanford.edu/class/cs224s/



http://www.ivline.info/2010/05/quick-guide-to-ecg.html

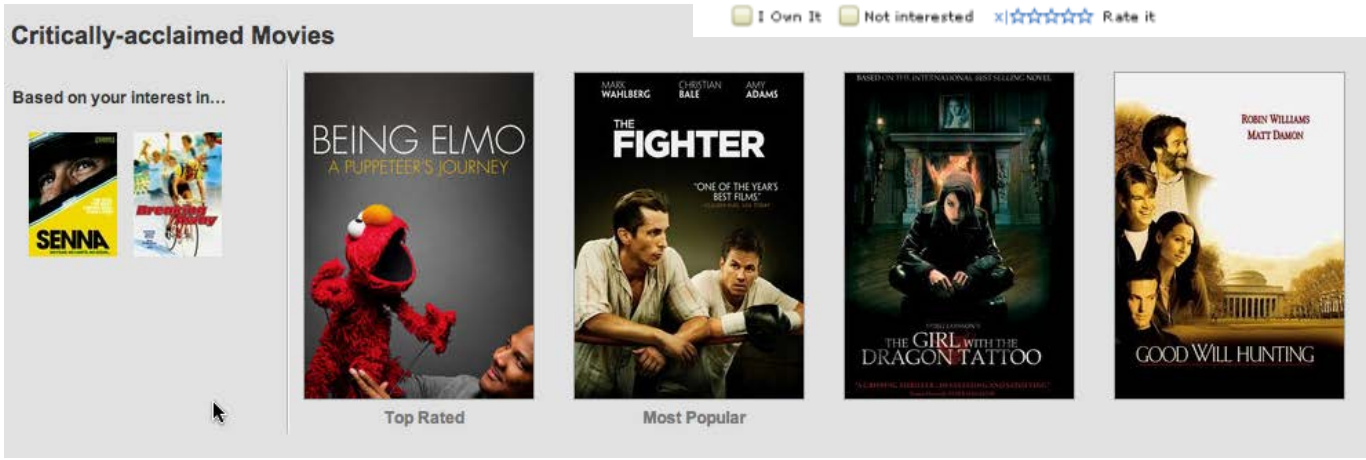
http://www.l1id.com/pages/116-face



http://networkprogramming.wordpress.com/2009/09/

Recommender systems

An effective way to enhance customer shopping experience and increase sales



Summary

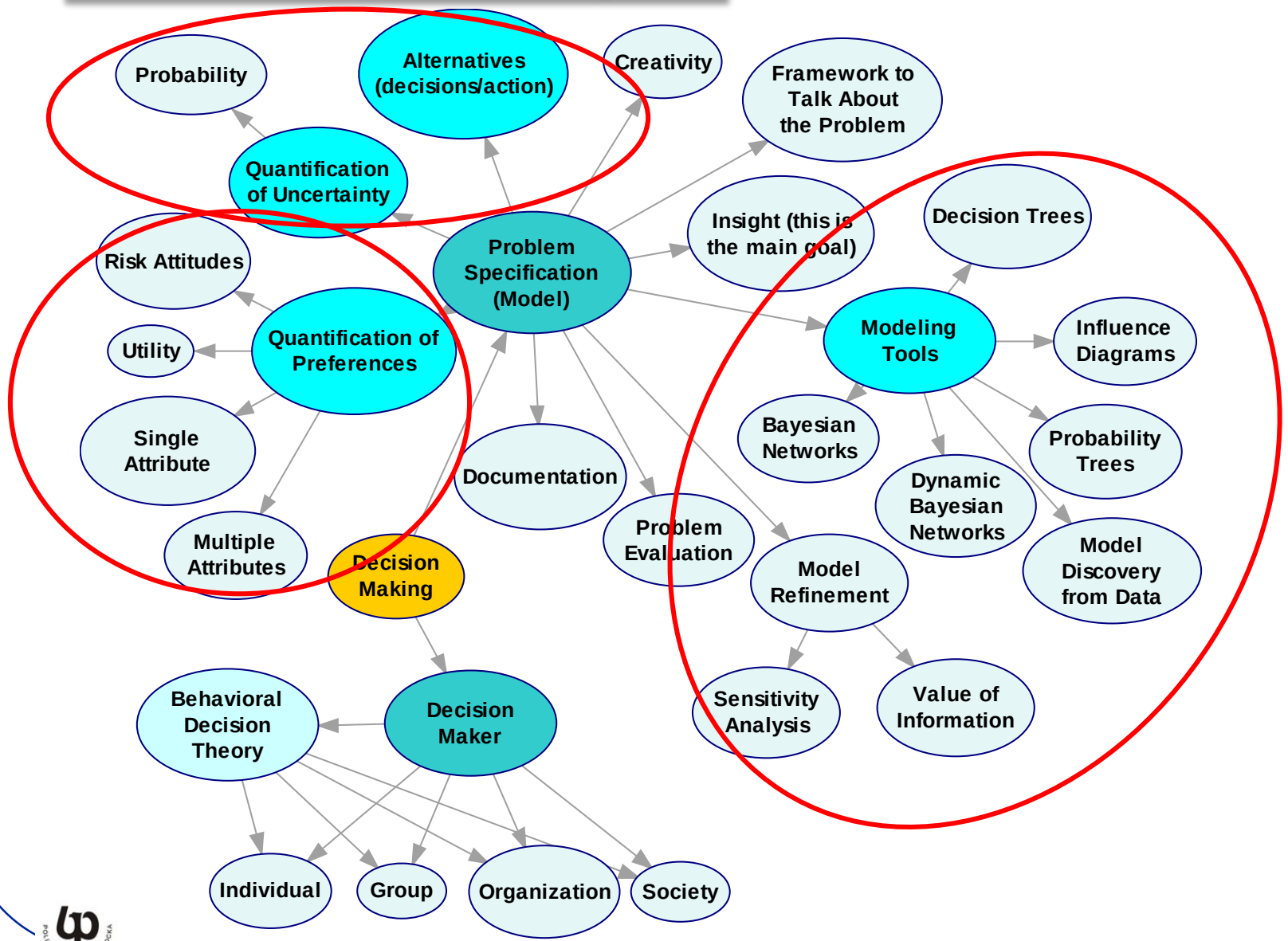
- It is not straightforward to define a good decision
- Decisions are hard
- Decision theory is a mathematical theory of how to make rational decisions
- Decision analysis is the art and science of applying decision theory in practice
- 21st century is the century of Bayes (but also of data ☺)
- There are many practical applications of the theory

Course Outline

What we will do in this course?

- In this course, you will learn the principles, how to create models of decisions and how to solve these models.
- All this is amenable to automation.
- The theory is general, applicable to all familiar AI problems of agents. In Artificial Intelligence, they often used ad hoc treatment of problems. This is over now. People look at problems in a systematic fashion, using normative tools.

Course relevance diagram



Course outline

PART I: INTRODUCTION

October 25

Getting to know each other; organization and overview of the course. Decision making; uncertainty, preferences, and actions; motivation for decision support; decision support systems. Rationality, rational behavior; good decisions vs. good outcomes; foundations of decision-analytic approach to decision support.

Course outline

PART II: BAYESIAN NETWORKS

November 15

A brief overview of useful statistical techniques.

November 22

Bayesian networks.

Introduction to GeNIe and SMILE©.

November 29

Structuring decisions, causality and probability.

December 6

Subjective probability, elicitation of probabilities.

Canonical probability distributions: Noisy-OR, -MAX, -AND, -MIN, DeMorgan gates.

(non)Importance of precision in numerical parameters.

Clarity test, sensitivity analysis, value of information.

Course outline

PART III: LEARNING BAYESIAN NETWORKS / CAUSAL DISCOVERY

December 13

Learning Bayesian networks/causal discovery.

December 20

Model validation techniques.

Course outline

PART IV: MODELING PREFERENCES

January 10

- Risk attitudes.
- Quantification of preferences.
- Expected utility theory.
- Utility elicitation, sensitivity analysis, value of information.

January 17

- Conflicting objectives: basic techniques, multi-attribute utility functions.

January 24

- Influence diagrams.