Models for decision making: From applications to mathematics... and back

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HEC Management School
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Francqui Lecture, KUL, March 2010

Outline

1. Mathematics and the real-world
2. Operations research and models
3. A glimpse at the lectures

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  - (Teacher) “What do you do these days?”
  - (YC) “Well, I’m spending more and more time working on real-world applications”
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- Opinion of a (mathematician) colleague:
  - “Mathematics should not be applied.”
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Historical point of view

And yet, historically: development of mathematics tightly linked with real-world (dirty) applications:

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It was an important task for the rulers of Mesopotamia to dig canals and to maintain them, because canals were not only necessary for irrigation but also useful for the transport of goods and armies. The rulers or high government officials must have ordered Babylonian mathematicians to calculate the number of workers and days necessary for the building of a canal, and to calculate the total expenses of wages of the workers. There are several Old Babylonian mathematical texts in which various quantities concerning the digging of a canal are asked for. (K. Muroi, Historia Sci. (1992))

Historical point of view

Arabic mathematics:

Arabic mathematicians, and in particular al-Haytham (965-1039AD) investigated the optical properties of mirrors made from conic sections.

Astronomy, time-keeping and geography provided other motivations for geometrical and trigonometrical research.
For example Ibrahim ibn Sinan (908-946 AD) and Thabit ibn Qurra (836-901AD) both studied curves required in the construction of sundials. Abu'l-Wafa (940-998AD) and Abu Nasr Mansur (970-1036AD) both applied spherical geometry to astronomy. (www-history.mcs.st-and.ac.uk)

Historical point of view

The word “algorithm” derives from the name of Al-Khwarizmi (780-850 AD) who was interested in teaching

> *... what is most useful in arithmetic, such as men constantly require in cases of inheritance, legacies, partition, lawsuits, and trade, or where the measuring of lands, the digging of canals, geometrical computations, and other objects of various sorts and kinds are concerned.* (www-history.mcs.st-and.ac.uk)

More recently

- Famous mathematicians like Newton, Lagrange, Gauss, Von Neumann were concerned with real-world problems as well as with pure mathematics, and constantly fed one type of research with the other one.
- (Which is not to say that they did not make any difference between pure and applied mathematics, but rather that they showed no disdain for either activity.)

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Management and economics

Mathematical models and methods play a useful role in management and economics:

- game theory and theory of social choice,
- microeconomics,
- econometrics, statistics,
- pricing of financial instruments,
- actuarial theory,
- operations research,
- etc.

Operations research

The science of better

Operations research is the discipline of applying advanced analytical methods to help make better decisions.

- By definition: focuses on applications and on action.
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Finalists of Edelman Award for Achievement in OR

- Hewlett Packard: "Product Portfolio Management with OR"
- IBM: "OR Improves Sales Productivity at IBM."
- Marriott International: "Group Pricing Optimizer."
- Zara Uses OR to Reengineer Its Distribution Process
- Netherlands Railways: "The New Dutch Timetable: The O.R. Revolution"
- Federal Aviation Administration: "Airspace Flow Programs"
- StatoilHydro and Gassco: "Optimizing the Offshore Pipeline System for Natural Gas in the North Sea"
- The City of Stockholm: "O.R. Improves Quality and Efficiency in Social Care and Home Help"
- U.S. Environmental Protection Agency: "Reducing Security Risks in American Drinking Water Systems"

Closer to us...

Closer to us...

Scheduling the Belgian soccer league (D. Goossens, F. Spieksma)

- Algorithm actually used to schedule the first division (Jupiler league)
- Takes into account the wishes of the clubs, of the police, and of TV broadcasters
- Increases the transparency of the process

Closer to us...

NSide (joint spinoff UCL - ULg)

SCOOP: Steel Cost Optimization

- A strategic decision support tool
- Aimed at selecting the best combination of raw materials that match all quality and technical requirements of an integrated steel plant
- Reducing the raw material costs by a fraction of percent translates into huge savings.
- Already adopted by plants in Belgium, France, Germany, Brazil, Czech Republic

Closer to us...

NSide (joint spinoff UCL - ULg)

Electricity markets

- Collaboration with Belpex (Belgian power exchange)
- Challenge: clearing of day-ahead electricity market for coupled (integrated) markets in Netherlands, Belgium and France – balancing cross-border energy exchanges at equilibrium prices.
- Solution adopted by consortium on the basis of an international competition.

Closer to us...

Gambit Financial Solutions
(spinoff ULg)

GAMBIT
FinancialSolutions

Investor profiling

Objectives:

- quantify an individual's attitude toward risk,
- define and manage optimal investment portfolios that are consistent with the risk profile.
- Based on modeling and optimization of utility function
- Complies with regulations for retail investment products ("knowledge of clients' profile").
- Solution adopted by several financial companies.

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Models in science

Operations research (like much of modern science) relies on

- mathematical models as idealized, or schematic representations of real-world situations,
- mathematical solutions of such models in order to obtain insights into the properties of alternative courses of action.

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Models in science

Because models are idealized and schematic, they may appear to some decision-makers as being disconnected from reality, and useless.


Ceci n'est pas une pipe.

Models in real life

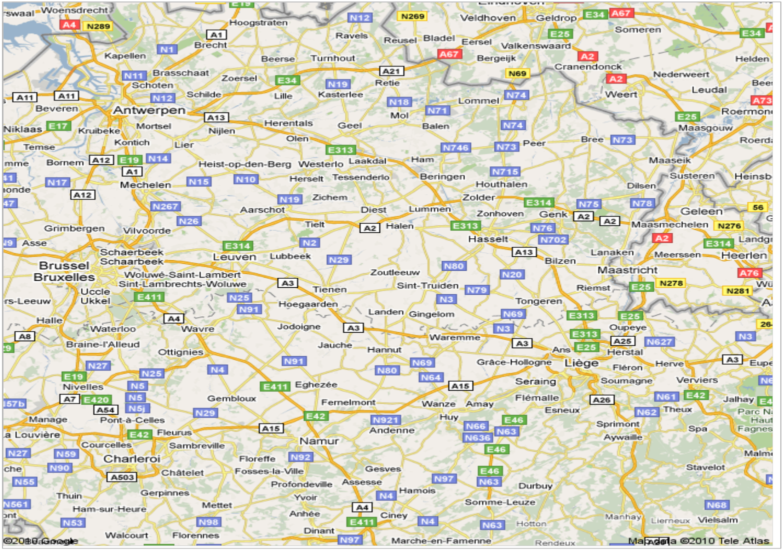
Models actually turn out to be very useful.. and we all use them everyday.

Example: route finder

Suppose I want to find the best way to drive from Liège to the center of Leuven.

A first model

Google maps Belgique



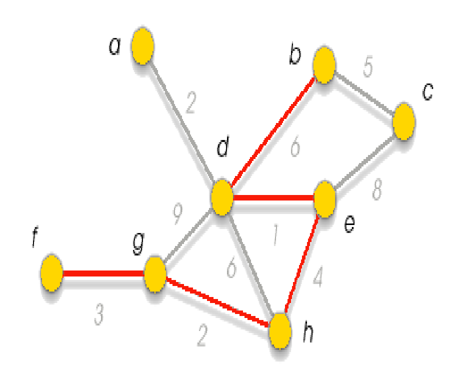
Example: route finder

A more detailed model

Google maps Belgique

Example: route finder

A mathematical representation as a graph



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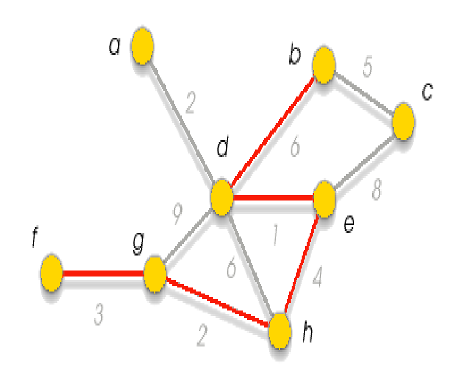

Shortest paths

Question:

Given a graph, with distances on its arcs, how do we find a shortest path from point A to point B?

Answer:

- Classical problem in operations research
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A more complete answer:

- New applications require very fast algorithms (on-line computation by the GPS navigation system in your car)
- for huge networks (route from Liège to Madrid)
- and for dynamic networks (traffic conditions, accidents, road construction work,...).
- Such questions foster new mathematical and computational developments (preprocessing of large networks, hierarchical approaches, etc.) which can be in turn incorporated in mobile navigation devices.

Typical example of the interplay between real-world problems, mathematical research and computational developments.

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Progress in combinatorial optimization

Last 50 years: much research on combinatorial models, or discrete models, meaning roughly:

- mathematical models involving a finite number of "states", or "configurations", or "solutions" (as opposed – roughly – to "continuous" models, such as those describing the position of a planet around the sun, or the temperature of a compound, or the voltage in an electrical circuit).

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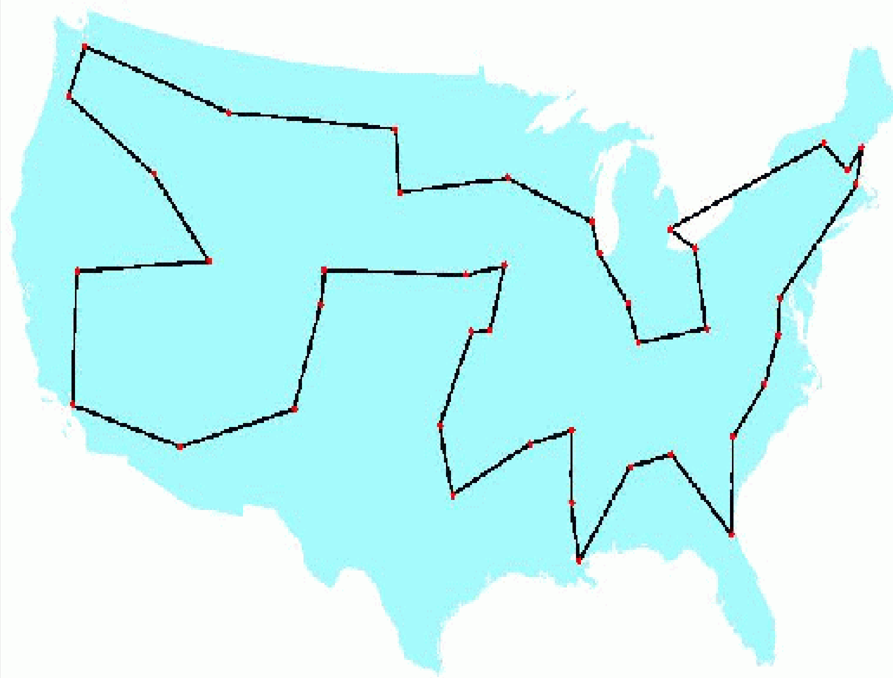
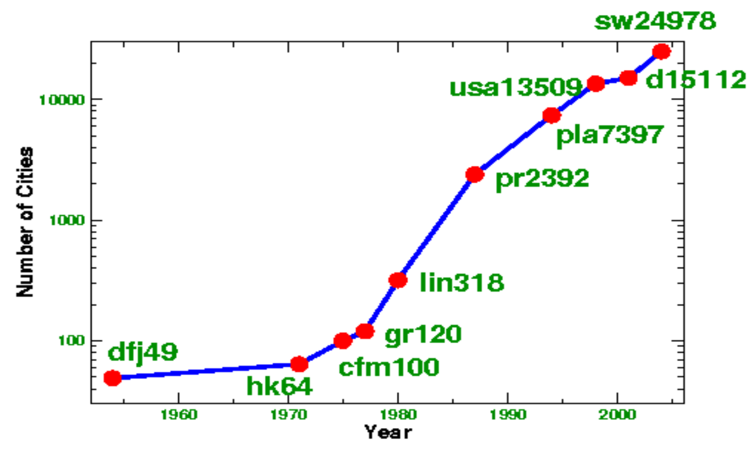
Traveling Salesman Problem

Find the shortest tour to be followed by a truck which is to deliver goods at a number of predefined locations.

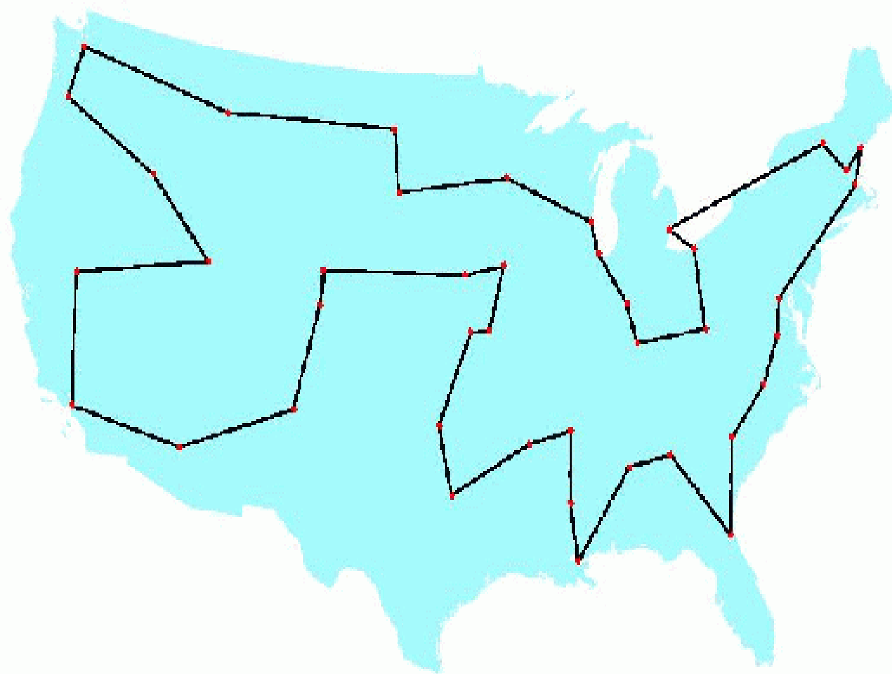


Progress in combinatorial optimization

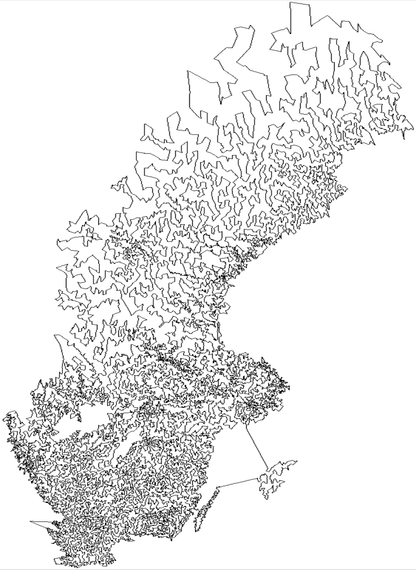
Illustration of progress on this problem from 1954 to 2004:



Dantzig, Fulkerson, Johnson: 49 cities (1954)



Applegate, Bixby, Chvátal, Cook: 25,000 cities (2004)



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- Nobody wants to visit 25,000 Swedish cities!
- A more realistic example: production of computer chips.
- Minimize the time required for a laser to interconnect the gates of the chip.
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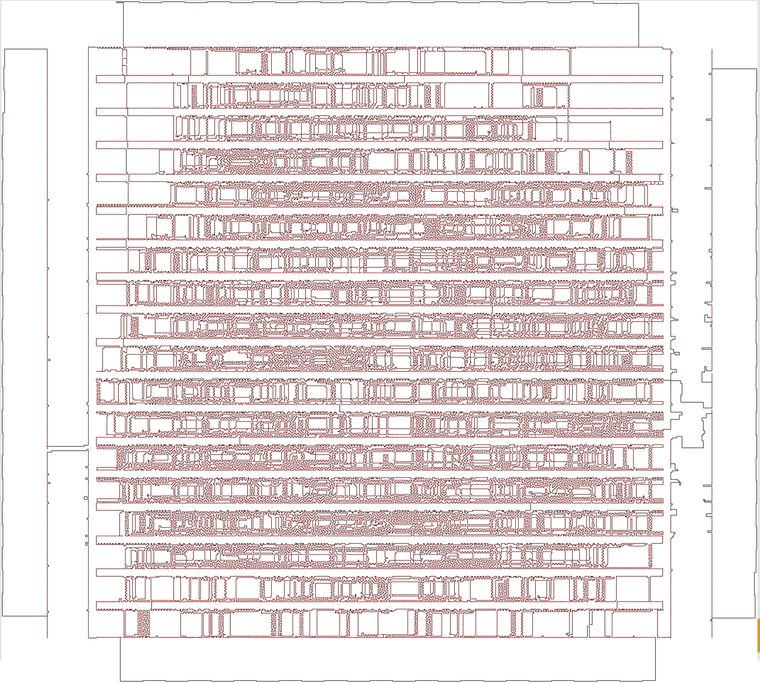

Progress in combinatorial optimization

Computing requirements

- About 1.5 years of computing time on 250 parallel processors,
- equivalent to 140 years of computing time on a powerful sequential processor.

Progress made possible by a combination of:

- advances in computer hardware,
- advances in implementations of complex algorithms,
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Similar progress has been observed in other areas of application (such as production planning).

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Globally: speedup by a factor of 1,000,000.
Problems which earlier required 1 year of computing time can nowadays be solved in 30 seconds.

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Boolean functions

Some mathematics...

A function is a rule F of the form:

$$(\text{input } 1, \ldots, \text{input } n) \rightarrow \text{output} = F(\text{input } 1, \ldots, \text{input } n)$$

It associates a value (output) with every possible combination of values given to n variables (inputs).

Examples:

- price $\rightarrow$ demand;
- labor and capital $\rightarrow$ production quantity;
- day of the year $\rightarrow$ height of the tide.

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Boolean functions

For a function to be interesting,

- a variable should take at least two distinct values (otherwise... it is not a variable), and
- the function should take at least two distinct values (otherwise... it is not a function of the variables).

So: the most elementary interesting functions are those where each input variable takes exactly two values and where the function itself can take exactly two values.

Such functions are named Boolean functions, after George Boole (1815-1864).

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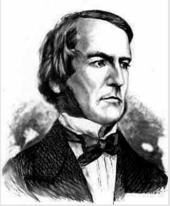


- George Boole was interested in modeling human reasoning (or the *Laws of Thought* – 1854).
- In a Boolean function, each variable, as well as the output of the function, can be viewed as representing the value True or False.
- In spite of their simplicity, Boolean functions have found an amazing array of applications over the last 150 years.

Applications of Boolean functions

- Artificial intelligence: an action is taken (Yes or No) depending on the presence or absence of certain features (e.g, medical diagnosis: prescribe additional tests or not)
- Electrical and electronic engineering: signal goes through a network (Yes or No) depending on the state of intermediate gates (Open or Closed)
- Computer science: computation output is 0 or 1 depending on the initial input (in binary format: string of 0's and 1's)
- Game theory and social choice: a resolution is adopted (Yes or No) by a governing body (e.g., by the Council of Ministers of the European Union) depending on the votes (Yes or No) of individual members.
- Reliability: complex system operates (Yes or No) depending on the state of its elements (operating or failed)

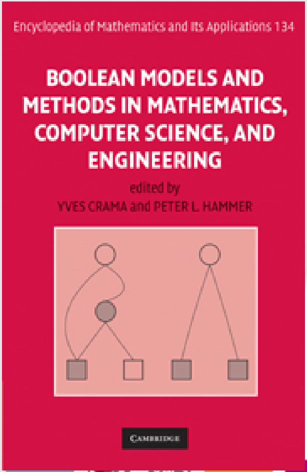
Some advertising...

Two forthcoming books on Boolean functions:

BOOLEAN MODELS AND METHODS in Mathematics, Computer Science and Engineering

Yves CRAMA and Peter L. HAMMER, eds.
Cambridge University Press
Due to appear: June 2010

About 750 pages



Some advertising...

BOOLEAN FUNCTIONS
Theory, Algorithms, and Applications

Yves CRAMA and Peter L. HAMMER
Cambridge University Press
Due to appear: December 2010
About 800 pages

Two Boolean models

1. **Analysis of shareholders' power in corporate networks** (YC, L. Leruth and S. Wang).
2. Classification: mining meaningful relations in databases (E. Boros, YC, P.L. Hammer, T. Ibaraki, A. Kogan, ...)

Analysis of shareholders' power in corporate networks

Problem statement

Given a large network of shareholding relations among firms, analyze the structure of control in this network.

Basic idea:

- Each shareholder can express his power by voting in general assemblies.
- His influence propagates in the network following shareholding links.

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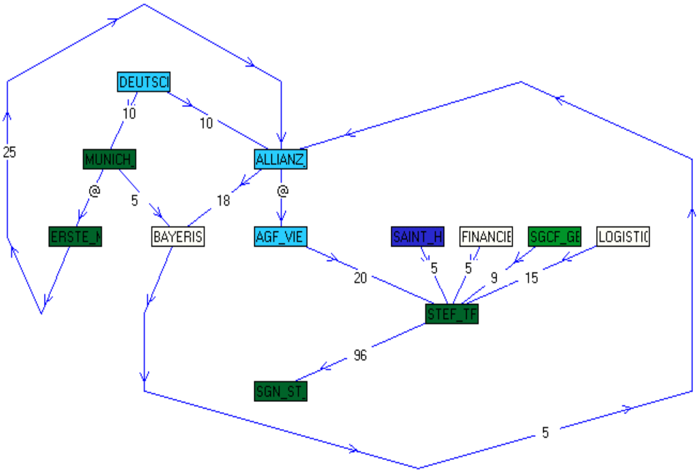
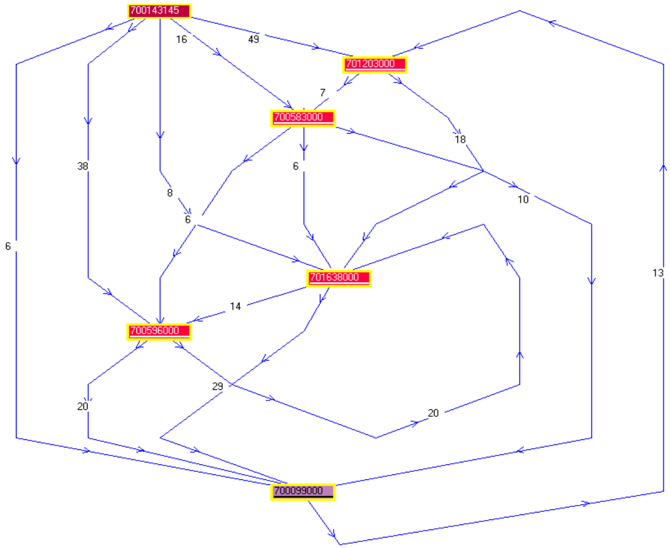
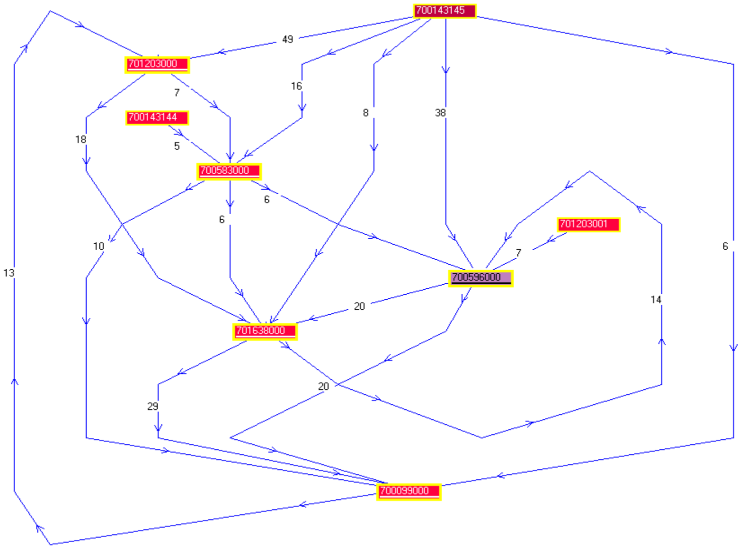


Shareholders' network 2



Shareholders' network 3



Analysis of shareholders' power in corporate networks

Combining

- game-theoretic models and measures of power,
- stochastic simulation to mimic the behavior of voters,
- graph-theoretic algorithms to accelerate computations,

allows us to

- define meaningful, rigorously defined concepts of shareholders' power;
- compute power indices in large-scale networks (much larger and more complex than allowed by other methods);
- automatically detect groups controlled by a given shareholder;
- automatically detect all shareholders holding power over a target firm.

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Two Boolean models

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2. **Classification: mining meaningful relations in databases** (E. Boros, YC, P.L. Hammer, T. Ibaraki, A. Kogan, ...)

Classification: mining meaningful relations

Problem statement

Given a collection of observed events together with concomitant circumstances, or attributes, explain/predict the occurrence of further events based on the values of the attributes.

Examples:

- List of past decisions regarding the decision to grant, or not to grant, financial credit to an applicant based on observed features (level of income, past credit record, education level, etc.). Objective: automate/objectify future decisions
- Classify benign vs. malign cancers based on collections of tests and past observations.
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Logical Analysis of Data

Boolean analysis framework developed in

Y. Crama, P.L. Hammer and T. Ibaraki,
Cause-Effect Relationships and Partially Defined Boolean Functions,
Annals of Operations Research 16, 1988, 299-325.

Basic idea:

- express the relation to be learned as a Boolean function (outcome is Yes or No depending on the values of the attributes) and
- try to “guess” the most appropriate functional representation which fits the observed data.

Logical Analysis of Data

LAD has generated a constant stream of (pure and applied) research over the last 20 years, in connection with related developments in data mining and machine learning.

Main advantages:

- model obtained is comprehensible, understandable by a human being (logical classification rules are explicitly generated);
- takes into account the interactions among features, rather than individual effects only.

A typical application of LAD:

G. Alexe et al., Ovarian Cancer Detection by Logical Analysis of Proteomic Data, *Proteomics* 4, 2004, 766-783.

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A typical application of LAD

- Observations: 162 ovarian cancer (positive) cases, 91 control (negative) cases
- Features: 15,154 peptides
- Data: Mass spectroscopy measurements for all peptides

Based on the analysis:

- only 7-9 peptides are needed to describe the classification;
- accuracy of classification is very high: about 98-99% of correct classifications;
- classification rules raise new research questions for biologists (how and why are certain patterns related to the occurrence of cancers?);
- classification rules allowed to detect two (previously unknown) main classes of cancers, based on peptide values.

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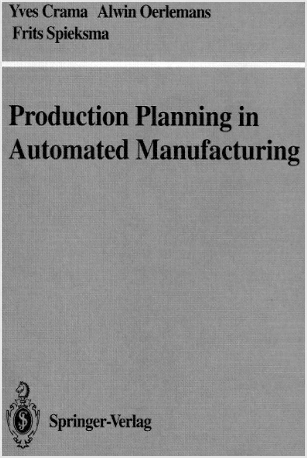
Topics

Lectures focus mostly on two types of models:

- Boolean models;
- **production planning and scheduling models.**

More advertising...



Springer, Berlin, 1996
Second, revised and enlarged edition.

Production planning and scheduling models.

Interest in specific models arising in connection with “modern” production systems (joint work with Brauner, Grigoriev, Gultekin, Oerlemans, Oosten, Spieksma, Van de Klundert):

- tool management for flexible machines,
- production planning of assembly lines for printed circuit boards,
- scheduling operations of robotic production cells,
- balancing assembly lines,
- Just-in-Time production systems.

In particular, interest in the computational complexity of such problems:

- how much computation is required to obtain their optimal solution?

Production planning and scheduling models.

When viewed from an abstract mathematical point of view, these problems turn out to be related to, and raise questions about

- properties of special classes of (totally unimodular) matrices
- special classes of traveling salesman problems
- problems of fair apportionment of votes in electoral systems
- optimal use of memory space in computers (paging)
- deep (unsolved) mathematical questions in number theory
- etc.

Conclusion

Such connections underline again the fruitfulness of looking at real-world problems from a mathematical point of view... and conversely.

Conclusion

From applications to mathematics... and back

Thank you for your presence and for your attention.